Essays on Economics of Transport Infrastructure: Pricing, Investment and Competition

by

Kun Wang

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Business Administration)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

August 2018

The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

Essays on Economics of Transport Infrastructure: Pricing, Investment and Competition

submitted by Kun Wang in partial fulfillment of the requirements

the degree of Doctor of Philosophy

in Business Administration

Examining Committee:

Anming Zhang, Sauder School of Business

Supervisor

Robin Lindsey, Sauder School of Business

Supervisory Committee Member

Ralph Winter, Sauder School of Business

Supervisory Committee Member

Kevin Milligan, Vancouver School of Economics

University Examiner

Thomas Davidoff, Sauder School of Business

University Examiner

Additional Supervisory Committee Members:

Tae Hoon Oum, Sauder School of Business

Supervisory Committee Member

Abstract

This dissertation focuses on three major topics in transportation. The first one is related to the seaports adaptation to climate change related disasters (Chapter 2). We investigate the disaster adaptation investments made by two landlord ports with each serving its captive markets while competing for a common hinterland. The impact of "Knightian uncertainty" of disaster occurrence on port adaptation investment is investigated. We also investigate the impacts of inter-port and intra-port competition and cooperation on the port adaptation investment.

The second topic is related to competition between airlines and high-speed rail (HSR) (Chapter 3). We investigate, both theoretically and empirically, the effect of HSR speed on airline traffic and price, taking into account the degree of air-HSR service substitutability. We consider two countervailing effects of HSR speed on airlines, i.e., the "travel time" effect and the "safety" effect. A rare natural experiment in HSR speed reduction in China is used to empirically test the theoretical findings. The incident is a rare quasi-natural experiment of HSR speed change as it was forced by the government due to safety concern and implemented system-wide regardless of market heterogeneity. A difference-in-differences method is used for estimation of the HSR speed effect on airlines as well as for verification of the theoretical predictions.

The last topic addresses two important issues in the air transport economics, aiming to provide new insights. In Chapter 4, we develop a structural discrete-choice model to study airline competition in Chinese domestic market, explicitly taking into account the potential effects of "legacy" regulation on airlines' competition behavior. Finally, in Chapter 5, we explore the effect of airport congestion on airport's concession revenue. We model and empirically test two countervailing effects of airport congestion on airport concession demand: namely a "dwell time" effect (passenger spends more, due to longer dwell time within the airport) and a "stress" effect (passenger spends less when he/she feels stressful because of the congestion). The implications on airport optimal pricing and social welfare are investigated.

Lay Summary

This dissertation studies three major topics emerging in today transport sector, especially in the fast-growing markets. The first topic is on seaport adaptation to climate change related disasters. It shows how the disaster uncertainty, and port competition and cooperation can affect optimal port adaptation investment, and the resultant implication to social welfare. The second topic is about the airlines and high-speed rail competition, in which we examine how the HSR speed can affect airline demand and price. Last topic is to explore how the government regulation can restrict airlines competition and the effect on airfare; and how airport congestion can affect passengers' concession consumption at the airport. Overall, our findings can contribute to a better understanding on these emerging issues in transportation, provide both policy and managerial implications, and open avenues for future studies as well.

Preface

A version of Chapter 2 has been accepted for publication. Wang, K., Zhang, A. (2018). Climate change, natural disasters and adaptation investments: Inter- and intra-port competition and cooperation. Transportation Research Part B: Methodological, forthcoming. Anming Zhang and I came up with the initial research question. I conducted the initial modeling analysis and all mathematical derivations. The first draft of the manuscript was written by me, and Anming Zhang made major revisions on later versions.

Chapter 3 is a joint work with Anming Zhang, Wenyi Xia and Qiong Zhang. A version of this chapter has been published. Wang, K., Xia, W., Zhang, A., Zhang, Q. (2018). Effects of train speed on airline demand and price: Theory and empirical evidence from a natural experiment. Transportation Research Part B: Methodological, 114, 99-130. Anming Zhang came up with the original research question. I proposed both theoretical economic model and econometric specification. I derived the basic theoretical economic model solutions, and worked with Wenyi Xia for further modeling extensions. The econometric part was exclusively done by myself. Anming Zhang made revisions on manuscript writing, and Qiong Zhang is responsible for data collection.

Chapter 4 is unpublished work jointly with Tae Hoon Oum and Xiaowen Fu. I came up with the research idea, derived the methodology, collected data and conducted estimation. Tae Hoon Oum and Xiaowen Fu helped on result interpretation and manuscript writing. A version of this chapter has also been awarded the "Best Graduate Student Paper" at the 58th US Transportation Research Forum.

Chapter 5 is unpublished work with Wenyi Xia, Tae Hoon Oum and Leonardo Corbo. I and Tae Hoon Oum came up with the research idea, developed and solved the economic model. Wenyi Xia and I conducted the empirical estimation. Leonardo Corbo collected data and contributed on manuscript writing. Tae Hoon Oum made major revision on the manuscript writing.

Table of Contents

List of Tables

List of Figures

Acknowledgements

I am deeply grateful and indebted to Prof. Anming Zhang, my thesis supervisor, for his always insightful and patient guidance on me to finish the major parts of my thesis. His enthusiasm in research and life inspired me all the way. I also would like to express my sincere appreciation to Prof. Tae Hoon Oum who was my chief supervisor in the first two years of my PhD study. He led me into the academic research, and always offers me the strongest support, both morally and financially. Using them as my role models, I have learnt the essence of integrity and hardworking to be a true scholar.

I would also express my sincere gratitude to Prof. Robin Lindsey and Prof. Ralph Winter, for their insightful advices provided to me on this dissertation and the PhD study, and spending their valuable time on serving as my thesis committee members. I also very indebted to Wenyi Xia, Prof. Xiaowen Fu for their great support and help on my work and provided advices on the chapters included in this dissertation, as well as Elaine Cho who has provided a wide range of timely and detailed administrative supports. My enduring gratitude also goes to my wife and parents who always love and support me unconditionally.

To my wife, Rongwen Jia

Chapter 1. Introduction

This dissertation includes three major research topics in transportation economics: (i). seaport investments for adaptation to climate change related disasters; (ii). airline and high-speed rail (HSR) competition; and (iii). airline competition and airport pricing. These issues are studied in four essays, which are Chapter 2 to 5 in this manuscript style dissertation.

The three topics in this dissertation are all motivated by current major challenges and recent development in the transport sector: the global climate change threat, the intermodal transport competition with dramatic HSR development, and newly emerging issues on aviation management. As the transport sector contributes significantly to the well-being of the society (i.e., employment, tax revenue, investment and economic output), and also provides indispensable inputs to other sectors such as logistics and trade, well developed and coordinated transport systems are of critical importance to the modern society. Major policy options and market competition strategies around the three topics have been implemented or proposed. Despite aiming to promote social welfare or improve financial performance, many of them have not been sufficiently studied. For some of the adopted policies and strategies, their ultimate effects, and underlying mechanisms remain unclear. For some of them proposed, there is a need to quantify the effects and benchmark with alternatives ex ante. This dissertation, therefore, aims to investigate the abovementioned three topics through rigorous economic modeling and econometric approaches, with the hope that optimal policies and strategies can be identified.

1.1 Port adaptation investment to climate change related disasters

Chapter 2 is the first topic. This research is motivated by the fact that the climate change has threated the resilience of the transport systems and the global supply chain, and seaports are especially vulnerable to climate changed related disasters. Given over 80 percent of global trade by volume and more than 70 percent of its value being carried by maritime shipping (UNCTAD, 2017), a better adaptation to climate change related disaster is vital to maintain the function of global supply chain and international trade. The past decade has witnessed more frequent extreme weather events and natural disasters around the world, resulting in increasing economic and social

costs, e.g., Katrina (occurred in 2005), Sandy (in 2012) and, most recently, Harvey (in 2017) on the US (United States) coastline. Scientific studies suggest that climate change might lead to an increase in both the occurrence and the strength of weather-related natural disasters in the near future (e.g., IPCC, 2013; Keohane and Victor, 2010; Min et al., 2011).

However, in spite of its growing importance of port adaptation, the research on this issue has been underdeveloped and provided limited insights on how to adapt port services to climate change related threats. In particular, the majority of existing literature focuses on environmental effects of transportation (especially the mitigation to reduce emissions of transport sector on climate change; see, e.g., Zhang et al., 2004; Wang et al., 2015; Liu et al., 2017). And a research line on the interplays between ports and their hinterlands is emerging (e.g. De Borger and Proost, 2012; Wan et al., 2016, 2017). However, these studies focus on the issues of port and hinterland pricing and capacity investment (Basso and Zhang, 2007; De Borger and De Bruyne, 2011). The impacts of the disaster uncertainty, inter- and intra- port competition and cooperation on port adaptations have been largely left untouched.

In Chapter 2, we develop an economic model to study disaster adaptation investments made by two landlord ports that serve their own respective captive markets while compete for a common hinterland. Each port consists of a private port authority (landlord owning the port infrastructure and land) and a private terminal operator (tenant owning the superstructure and handling the cargos). This landlord type port is the most common port structure in the world. We model the probability of a natural disaster, which is induced by climate change, to be ambiguous prior to an adaptation investment, but will be known after the adaptation investment, i.e., a "Knightian uncertainty" (Knight, 1921). [1] We assume this Knightian uncertainty of disaster probability in the sense that probability of the disaster occurrence is uncertain (a random variable) and not accurately knowable.

In Chapter 2, we find that (i). with Knightian uncertainty assumption, a higher expectation of the disaster occurrence probability encourages the adaptation, but the variance of the disaster occurrence probability can discourage the adaptation. This analytical result may provide a sound explanation for why in practice adaptation is much more difficult to implement than mitigation: it

[1] Knightian uncertainty refers to ambiguity in which decision maker has to make decisions when the relevant probabilities are unknown.

might be because our present knowledge about climate change and related disasters is far from reasonable accuracy; (ii). inter-port competition also results in more adaptation investments (i.e., the "competition effect"); (iii). there is free-riding on adaptation investments between the port authority and the terminal operator (i.e. the "free-riding effect") within each port. Their intra-port coordination can increase the adaptation by removing such free-riding effect; and (iv). these two effects can be strengthened by a higher expectation and larger variance of the disaster occurrence probability, and by a more intense inter-port competition (less service homogeneity).

Overall, this chapter has shown the complexity for port adaptation decision. On one hand, the great uncertainty of the disaster occurrence makes it difficult for ports to justify the adaptation investment. On the other hand, the port market structure (both vertical and horizontal relationships among the entities) has further complicated the strategic adaptation efforts. Besides the climate change disaster challenge, the following Chapters 3-5 examine the other major emerging issues on the transport sector. Same as Chapter 2, the following chapters also demonstrate very complex strategic interactions within transport sector among many involved entities.

1.2 Air-HSR competition

Chapter 3 addresses the intermodal competition between the airlines and the high-speed rail (HSR). This research was motivated by the recent phenomenal HSR expansions, especially in China. By the end of 2017, the length of HSR network under operation in China has reached 25,000 kilometers (km), greater than the sum of the rest of the world. China recently announced its plan to further expand its HSR network to a total length of 38,000 km by 2025, when all Chinese cities with more than half million population will have HSR linkage. At least a yearly investment of 800 billion RMB (about 115 billion USD) is required from 2017 to 2025 to maintain the pace of HSR expansion. This HSR development has intensified air-HSR competition dramatically. There have been several studies focusing on air-HSR competition in the European markets, where the HSR has longer history of development (e.g. González-Savignat, 2004; Behrens and Pels, 2012; Dobruszkes, 2011; Capozza, 2016). However, recently, intense air-HSR competition is mainly observed in the Chinese market, evidenced by the fact that the airlines were forced to cut prices and withdrew from several important routes (Fu et al., 2012; Jiang and Li, 2016). For example, air ticket price has dropped by 80% in the market between Wuhan and Xiamen, two provincial capital

Chinese cities recently linked by HSR. Spring Airlines, the largest of the low-cost carriers (LCCs) in China, withdraw all capacities from the routes less than 800 km to avoid head-to-head competition with HSR (Wang et al., 2017). The HSR has already outpaced the air transport growth in China, as the HSR passenger traffic grew at an annual rate more than 30% for the 2008-2016 period, while the air transport grew at only about 10% during the same period (Chinese Statistics Yearbook 2017).

However, in spite of the growing air-HSR competition, several issues have not been well addressed by existing literature. Especially we find there have been few studies to explicitly examine the HSR speed effect on airline demand and traffic. The answers to this question is of great policy relevance and managerial implications in that many countries are lifting the HSR speed. For example, China has decided to raise the HSR speed from current 300 km/hr (kilometers per hour) to its design speed at 380 km/hr, and the US, Japan and China are also developing maglev HSR with speed more than 500 km/hr. Furthermore, the HSR speed increase can also cause safety concern, which is an important factor for travel mode choice in developing countries where the HSR technology is immature. However, there are very limited studies that explicitly investigate how the HSR speed could affect air-HSR competition (in terms of airline traffic and price).

To fill these research gaps, in Chapter 3, we develop an analytical model to study HSR speed effects on airline traffic and price, explicitly accounting for the potential impact of intermodal substitutability between airline and HSR services in different markets. The model incorporates two countervailing effects of HSR speed on airlines, namely the "travel time" effect and "safety" effect, in that an increase in HSR speed reduces HSR travel time but may harm public confidence in HSR safety. Following the analytical model predictions, we empirically test and quantify the HSR speed effects on airlines using an event of HSR speed reduction in China. We utilize a quasi-natural experiment of the HSR speed reduction in China due to a fatal accident in 2011 for estimation. This speed reduction is an exogenous shock as it was implemented system-wide and enforced by the government rather than being a market competition outcome. A difference-in-differences method is employed to estimate equations of airline traffic and price. In line with theoretical analysis, we identify the varying HSR speed effects when airline and HSR services are differently substitutable. The theoretical model shows that (i). air-HSR substitutability reinforces the HSR speed effect on airlines; (ii). HSR speed has a larger impact on airline traffic than on airline price; and (iii). HSR speed effect can be moderated by the intensity of inter-airlines competition. The empirical results

are largely consistent with the theoretical propositions. Specifically, we find that (i). the HSR speed reduction increased both airline traffic and price, implying that the travel-time effect dominates the safety effect of a HSR speed change; and more importantly (ii). the estimation shows that the HSR speed effect on airlines is much stronger on short-haul routes than on long-haul routes, where airlines and HSR are less substitutable.

1.3. Air transport management and policy

The last parts of the dissertation aim to add to two emerging yet nascent research line on air transport economics: one is the airline competition under legacy regulation (Chapter 4), and the other is the impact of airport congestion on airport concession demand and pricing (Chapter 5). Chapter 4 is motivated by the fact that the air transport is growing dramatically in developing countries, especially with China becoming the world's second largest aviation market since 2005. However, most airline markets in the developing countries are still subject to restrictive regulations, such as route entry, airport slot allocation, capacity expansion etc. They lag far behind the developed countries, such as the US and the EU, in market liberalization. It is important to understand how such legacy regulations can distort airline competition and pricing in these developing countries. The presented research can help evaluate possible deregulation's effects on airlines pricing and passenger's surplus. we find that existing econometric approaches on airline studies assume a certain competition type, i.e. Cournot, Bertrand or collusion, and thus are unable to account for a wide range of airline competition behaviors under regulatory constraints. So in Chapter 4, we propose an improved econometric model to fill this research shortage. Besides, Chapter 5 is based on two dramatic trends in nowadays airport business: one is the increasing share of concession service revenue (i.e., services of retail, food and beverage, car rental, land rentals, car parking and advertising) in airport total revenue (Oum et al., 2004); and the other is the deteriorating airport congestion in major airports around the world (D'Alfonso et al., 2013; Wan et al., 2015). The interaction of these two factors (airport concession business and congestion) has been largely ignored, while there can be very essential implications on airport operation and pricing. On one hand, airport congestion can make passenger to stay longer at airport (increasing dwell time), thus increasing their chance to consume concession (D'Alfonso et al., 2013), but on the other hand, airport congestion can cause stress which may discourage the concession

consumption. The two countervailing effects of airport congestion on concession business have not been well explored.

Specifically, in Chapter 4, we develop a structural discrete-choice model to study airline competition in Chinese domestic market, explicitly taking into account the potential effects of legacy regulation on airlines' competition behavior. This work constitutes an improved econometric approach that allows researchers to identify a range of competitive regimes for different group of routes. This allows us to measure possible effects of the legacy regulation and to benchmark the results obtained under restrictive Bertrand or Cournot competition. The results show that (i). Chinese airlines set prices collusively on the densest (with highest traffic volume) routes where regulatory control is stricter and airport congestion is severer; by contrast, they compete more aggressively on less travelled routes with lighter regulatory control; and (ii). on model side, strong evidence exists that the presented new approach performs better than the existing competition models in terms of obtaining better results on estimation and prediction. This suggests that simply assuming a particular type of competition regime for a market may yield biased estimation. Our proposed econometric model may be also applied to other airline markets with legacy regulations, to identify the airlines competition behavior and for counterfactual analysis of possible market liberalization.

Finally, in Chapter 5, we explore the effect of airport congestion on airport's concession revenue, and optimal airport pricing on both aeronautical and concession services. We conduct both analytical and empirical investigations, proposing two countervailing effects of airport congestion on concession demand: (i). the "dwell-time" effect: passengers consume more when airport congestion forces them to stay longer at airport and (ii). the "stress" effect: passengers are unwilling to spend at airport when they are under stress caused by the flight delay or crowdedness. We propose an overall curvilinear effect of airport congestion on concession demand. Specifically, dwell time effect dominates when airport congestion is moderate, while stress effect prevails when airport congestion is severe. We then investigate the optimal aeronautical and concession charges of two types of airports: a private profit-maximizing airport and a public social-welfare maximizing airport. Our results suggest that (i). when airport congestion is severe and the stress effect prevails, it is possible that public airports charge a higher aeronautical price than private airports. This finding complements previous studies, which ignore airport congestion effect on concession demand and suggest that public airport always charges lower aeronautical price; (ii) empirical

evidence supports the existence of both dwell-time and stress effects of airport congestion on concession demand and price; and (iii) runway congestion contributes more to dwell time effect while terminal congestion contributes more to stress effect.

Chapter 2. Climate Change, Natural Disasters and Adaptation Investments

2.1 Introduction

The past decade has witnessed more frequent extreme weather events and natural disasters around the world, with increasing economic and social costs. The examples include the impacts of hurricanes Katrina (occurred in 2005), Sandy (in 2012) and, most recently, Harvey (in 2017) on the US (United States) coastline. In particular, Harvey brought an estimated $75 billion economic loss[2], and Sandy caused an estimated $36.1 billion loss. Scientific studies suggest that climate change might lead to an increase in both the occurrence and the strength of weather-related natural disasters in the near future (e.g., IPCC, 2013; Keohane and Victor, 2010; Min et al., 2011). According to Morgan Stanley research, until 2015, among the top-ten most costly hurricanes hitting the US, eight occurred after year 2000.[3] Such increasing frequency and strength of hurricanes in North Atlantic Basin can be attributed to temperature rise of the ocean due to global warming (IPCC, 2013). In addition to such "one shot" disasters, there is an increasing risk of coastal and marine natural disasters (in terms of frequency and intensity) such as the sea level rise (SLR) owing to climate change. By the end of this century the sea level may be 75-80 centimeters (cm) higher than today's level (Schaeffer et al., 2012). Seaports are highly vulnerable to coastal and marine natural disasters, and are exposed to climate hazards such as SLR and resultant flooding and storms due to climate change (OECD, 2016). For example, Kafalenos and Leonard (2008) estimate the vulnerability of ports in the US Gulf Coast to SLR, and Nicholls et al. (2008) assess the exposure to flooding for 136 large port cities around the globe. Stenek et al. (2011) and Scott et al. (2013) gauge the vulnerability for port system sub-components to climate-change, including navigation, berthing, material handling, vehicle movement, goods storage and transportation. The increasing risk of natural disasters to seaports may trigger substantial social, economic loss and may lead to shifts in freight transport and passenger flow (Koetse and Rietveld, 2009). Crucially, many ports play a critical role in global supply chains, so that any significant loss or degradation of service due

[2] Unless specified otherwise, the dollar amount in this chapter is in US$.

[3] The details about top ten most costly hurricanes in the US can be found in the link http://www.businessinsider.com/hurricane-irma-costliest-hurricanes-us-history-map-2017-9.

to disaster occurrence would have significant knock-on effects on global supply chain performance (OECD, 2016).

Unlike rich literature on the environmental effects of transportation (especially the mitigation of transport sector on climate change; see, e.g., Zhang et al., 2004; Wang et al., 2015; Liu et al., 2017), there is a lack of research on the adaptation of ports to climate change related disasters. [4] Xiao et al. (2015) is one exception that models the port adaptation investment by both port authority and terminal operator under the uncertainty of disaster occurrence. They find that there is a free-riding effect of adaptation efforts between the two entities, and that the information of the disaster occurrence is essential for the timing of adaptation investments (the "invest now or later" question). It is noted that Xiao et al. (2015) consider port adaptation of a single port and so they did not consider inter-port competition [5]. They further treat port demand and pricing being exogenous to adaptation investments. However, port adaptation and resilience to natural disaster can essentially affect port competitiveness and the port choice decision by shippers. For instance, port disruption can cause serious reputational and direct economic losses on shippers (Zhang and Lam, 2015), leading to their switching to a better adapted port for services (Chang, 2000). [6] Therefore, an improved theoretical model on port adaptation need to endogenize the shipper's demand and port pricing decisions, and incorporate the inter-port competition as well.[7]

[4] There are several studies on post-disaster relief, and transport and logistics system resilience (e.g. Chen and Yu, 2016; Huang et al., 2013; Rawls and Turnquist, 2010; Sheu, 2014), while the studies on adaptation strategies are few. In addition, these studies mainly adopt engineering approaches to analyze optimal cargo flow and to strengthen the important segment of the supply chain or network for enhancing the network resilience, and the economic analysis is not well implemented.

[5] Port competition and cooperation was recently also analyzed in disaster prevention by Liu et al. (2017), in which the ports can be either substitutes or complements. They focused on the case of mitigation rather than adaptation, however.

[6] For example, Chang (2000) empirically studied the impact of the 1995 Great Hanshin earthquake on the port of Kobe (Japan), which was shut down post the disaster and only recovered after two years. She found that due to the earthquake damage, the Kobe port lost most of transshipment cargo to competing Asian ports, in both the short- and long-term.

[7] Theoretical analyses on port competition and the interplays between ports and their hinterlands are emerging. Wan et al. (2018) reviewed recent theoretical studies in the area, and found that these studies mainly focus on the port and hinterland capacity investments, and on port congestion pricing (De Borger et al., 2008; Zhang, 2008; De Borger and Proost, 2011; Wan and Zhang, 2013). Some recent studies discussed the emission control of marine transport, such as Homsombat et al. (2013), Wang et al. (2015), Sheng et al. (2017) and Dai et al. (2018). However, none of these papers have considered port adaptation to climate-change risks.

Furthermore, despite a rich theoretical literature on traffic demand uncertainty modelling,[8] uncertainty about climate change-related disasters and the associated costs have not been well modeled in existing maritime transport studies. Uncertainty regarding their occurrence and outcomes can be very high (IPCC, 2013; OECD, 2016), due to limited scientific knowledge and to forecast complexity. In contrast, traffic demand can be more accurately forecasted with the availability of rich historical traffic data and other economic and demographic variables. Therefore, to model uncertainty of climate change-related disasters, one needs to account for the large ambiguity at the adaptation planning and investment stage, noting that adaptation projects usually are lengthy in duration and very costly. Xiao et al. (2015) modelled the disaster uncertainty in a two-period setting, assuming a uniformly distributed disaster occurrence probability in the first period but, with information learning, a more accurate (a more narrowly-bounded uniform distribution) probability in the second period. There is thus an option value in delaying investment, owing to better information about the disaster occurrence probability. However, this assumption of uniformly-distributed disaster occurrence probability could be restrictive. In this chapter, we propose a model allowing a general distribution of the disaster occurrence probability, which can capture the "ambiguity" notion of disaster uncertainty that is absent in Xiao et al. (2015).

Taken together, the present chapter contributes to existing literature by developing a more general analytical framework to analyze port adaptation to climate change-related disasters. More specifically, we model the climate change-related disaster occurrence probability to have Knightian uncertainty (Knight, 1921) at an early adaptation investment stage when two ports make adaptation decisions. Knightian uncertainty refers to ambiguity in which a decision maker must make decisions when the relevant probabilities are unknown. This is used to capture the fact that the probability of disaster occurrence is very uncertain (is subject to a probability distribution) at the adaptation planning stage. Our Knightian uncertainty is general and covers a wider family of probability distributions of natural disaster occurrence, which are not limited to the specific

[8] See, for example, the studies by Kraus (1982), D'Ouville and McDonald (1990), Proost and Van der Loo (2010), and Xiao et al. (2013). Kraus (1982) considered highway pricing and capacity choice under demand uncertainty, and found that both capacity and price are greater than those under an expected value of demand. D'Ouville and McDonald (1990) also studied the optimal capacity and toll of urban highways under demand uncertainty, and found that a social planner who simultaneously chooses the capacity and congestion toll to maximize the expected welfare will choose a larger capacity relative to the mean level of road use. Proost and Van der Loo (2010) examined capacity choice by modeling a social planner's decision on transport infrastructure capacity when the future demand can be either high or low, with different tolls being set for each case to maximize welfare. Xiao et al. (2013) analyzed the effects of demand uncertainty on airport capacity choices.

assumptions in Weitzman (2009) and Xiao et al. (2015). [9]The effects of this Knightian uncertainty on port adaptation are investigated. Moreover, the present chapter will explicitly examine the impacts of both inter-port competition and intra-port cooperation on port adaptation by explicitly modelling the *endogenous* port pricing and shippers' demand together with port adaptation. It is the first chapter, to our best knowledge, that analytically examines how inter-port competition would affect port adaptation.[10]

We find, with Knightian uncertainty assumption, port adaptation investment increases with the expectation of the disaster occurrence probability but decrease with its variance. In other words, a higher expectation of the disaster occurrence probability encourages the adaptation, but the variance of the disaster occurrence probability can discourage the adaptation. This analytical result is general and not limited to the specific disaster occurrence probability distributions assumed in Weitzman (2009) and Xiao et al. (2015), and it may provide a nice explanation for why in practice adaptation is much more difficult to implement than mitigation, owing to the fact that our present knowledge about climate change and related disasters is far from reasonable accuracy. Inter-port competition also results in more adaptation investments (i.e., the "competition effect"). This is an important supplementary finding to Xiao et al. (2015) who ignore the inter-port competition and its possible effect on port adaptation investment. There is free-riding on adaptation investments between the port authority and the terminal operator (i.e. the "free-riding effect") within each port. Their intra-port coordination can increase the adaptation by removing such free-riding effect. These two effects can be strengthened by a higher expectation and larger variance of the disaster occurrence probability, and by a more intense inter-port competition (less service homogeneity).

The chapter is organized as follows. Section 2.2 introduces the basic economic setup. Section 2.3 derives the analytical results for optimal port adaptation with different inter-port competition and intra-port coordination conditions. Section 2.4 examines the effects of inter-port competition

[9] As can be seen later in the model set-up for the adaptation investment stage, this Knightian uncertainty on the disaster occurrence probability can be integrated with the uncertainty of the disaster occurrence (Bernoulli trial) together, keeping the modeling set-up the same. Thus we can regard that the shippers are faced with an uncertain absolute level of disaster damage because of the total disaster uncertainty, including both the Knightian uncertainty on the disaster occurrence probability and the occurrence of the disaster. Thys, alternatively, we may use only one random variable to capture such total disaster uncertainty.

[10] Different from Xiao et al. (2015) with a multi-period investment model, the present paper abstracts away the issue of adaptation investment timing (the option value to choose to invest early or late).

intensity (port service homogeneity) on adaptation investments, and Section 2.5 contains the concluding remarks for this chapter.

2.2 Basic Model

We consider two nearby ports sharing a common hinterland that are subject to a threat of common but uncertain disaster (shown in Figure 2.1). The ports are of the landlord type, each consisting one port authority owning the port basic infrastructure, and a terminal operator as a tenant to own the port superstructure and directly handles cargo transport (Liu 1992).[11] The landlord port is the the most predominant type of ports in the world (Becker et al., 2012; Xiao et al., 2015). For landlord type port, the terminal operators are private entities. For example, PSA International, Hutchison Port Holding, APM terminals, DP World and China Merchant Holding are the major terminal operator corporations operating worldwide [12]. Port authorities are also assumed to be private entities to maximize profit, which is similar to Chen and Liu (2014) and Liu et al. (2018). Since 1990s, there is trend around the world to privatize port authority from public sector, aiming to relieve government's heavy financial burden, and to upgrade port operation efficiency (Liu, 1995; Cullinane et al., 2005). Port authority privatization was pioneered by the UK Thatcher's government in 1990s (Baird and Valentine, 2006). Later, corporatization of port authorities has been widely applied around the world, especially in Asia and Oceania (Everett, 2005; World Bank, 2011). Even without full privatization, most of port authorities have been corporatized, with government controlling partial share. Meanwhile, port governance has also been transferred from the national/state governments to local ones who are responsible for own financial performance

[11] There is no universally accepted framework for port classification. A widely adopted classification is by Liu (1992) to categorize port into four types: service port, tool port, landlord port and private port. A service port is if the port authority is responsible for the provision of all port facilities; a tool port is if the port authority is public and provides the infrastructure and superstructure, while the provision of services is licensed to private operators; a landlord port is in which the domain of the port authority (public or private) is restricted to the provision of the infrastructure, while investment in the superstructure and port operation is the responsibility of licensed private companies; a private port is if the provision of all the facilities and services is left to one single private entity.

[12] These operators are international corporations having business in many ports around the world. One operator may operate in two nearby ports at the same time (for example, Hutchison Port Holding operates in both Hong Kong and Shenzhen ports). One port can also have multiple terminal operators. To make the model tractable and to focus on the main trade-off issues, we assume that there is only one terminal operator for each port and that the two operators are independent.

(Cheon et al., 2010).[13] As a result, the port authorities would be profit-oriented, resembling a private entity to certain degree.

The two ports can belong to competing port authorities. Such inter-port competition is exemplified by the Pearl River Delta with Hong Kong port competing against Shenzhen port to be the gateway for South China. The other example may be the west European ports, especially the Hamburg-Le Havre (HLH) port range with several ports competing as the gateway to West and North Europe. One monopoly port authority to control multiple ports is also common. For example, Port Authority of New York and New Jersey controls port of Newark, Port of Perth Amboy and Port of New York. Georgia Ports Authority controls Port of Savannah and Port of Brunswick on the east coast of the US.

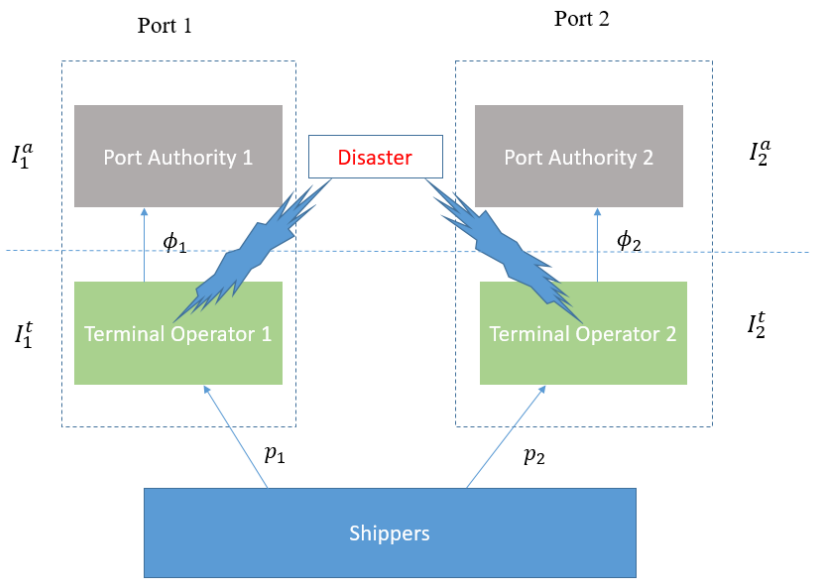
For landlord port, port authority signs concession contract with private terminal operator, stipulating the duration, concession fee scheme and other terms to lease the port land and basic facility to terminal operator (Trujillo and Nombela, 2000). Notteboom (2006) summarizes common types of concession contracts between port authority and terminal operator. Detailed concession fee scheme varies among the ports, but commonly, port authority charges a concession fee to the terminal operator based on the throughput it handled i.e. a unit concession fee, such that the total concession fee is proportional to the cargo volume.[14] Analogous to Basso and Zhang (2007), Pels and Verhoef (2004) [15], it is assumed that port charges within a port are determined in a vertical structure: the port authority decides a unit charge (unit concession fee) on the terminal operator first, and then the terminal operator chooses its unit service charge to be paid by shippers.

[13] According to Cheon et al. (2010), in 1991, 42% of the world's major hub and gateway ports were managed by national or state government bodies; by 2004, the percentage dropped to mere 32%. Corporatized port authorities accounted for less than 1/3 in 1991, but by 2004, the number became 45%.

[14] De Monie (2005) specifies three most common port authority concession fee schemes: unit fee, fixed fee and two-part tariff. Chen and Liu (2014) and Liu et al. (2018) analytically discuss and compare these three schemes for a port authority to maximize profit. They find that unit fee is most likely to be preferred by a profit maximizing port authority.

[15] Basso and Zhang (2007) study revelry between two congested facilities considering the upstream as the provider of the facility infrastructure and downstream carrier to use the facility. The pricing is determined in a vertical structure with downstream carrier charges the end customer, while upstream facility infrastructure provider charges carrier.

Figure 2.1 The market structure of the two-port system

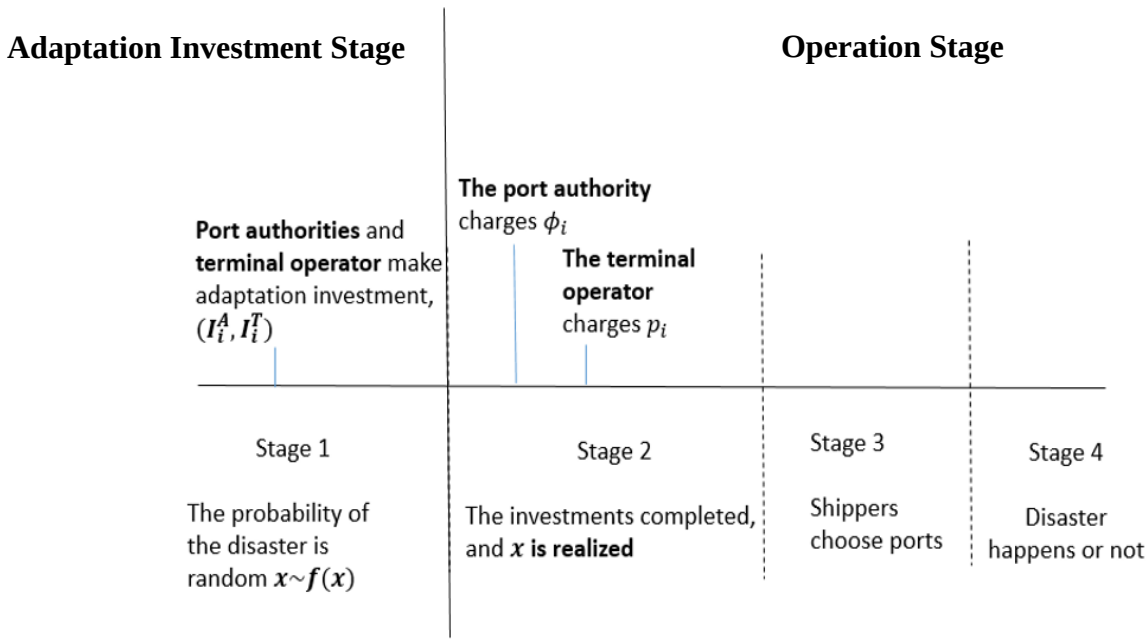


In this study, we model the impact of port authority inter-port competition and monopoly, and intra-port cooperation between port authority and terminal operator within one port, on port adaptation. A multi-stage game is used to model both an "adaptation investment stage" for the ports, and an "operation stage" when port charges are determined, conditional on adaptation investments.[16] The timeline of economic model is demonstrated in Figure 2.2. The probability of disaster occurrence is assumed to be ambiguous at adaptation investment stage, which is a Knightian uncertainty (Knight, 1921; Camerer and Weber, 1992; Gao and Driouchi, 2013; Nishimura and Ozaki, 2007). Knightian uncertainty suggests disaster occurrence probability x can be a random variable at adaptation investment stage, with a density function (pdf) $f(x)$, expectation Ω and variance Σ. But this probability only becomes realized later at operation stage when ports decide price and shipper chooses port. This improvement in information reflects a likely setting in which a better knowledge on climate change and related disasters is accumulated during the lengthy period of adaptation investment. At adaptation investment stage, port authorities and terminal operators at the two ports simultaneously determine their adaptation investment I_i^a , I_i^t . Once decided, the adaptation

[16] A multi-stage game is a widely adopted approach to model the capacity investment at early stage and pricing at later stage for transport infrastructure (e.g., marine ports and airports) such as Luo et al. (2012) and Xiao et al. (2013).

investments are assumed to be fixed since any adjustment would require additional complex evaluation and funding approval, thus causing major delay in completion. We do not consider the case where the disaster occurs during the period of adaptation constructions. However, this does not alter strategic behavior of the ports since both port authorities and terminal operators do not adjust pricing until the port adaptation is installed to take effect to reduce disaster damage.

Figure 2.2 The timeline of the decisions of different parties



At operation stage, following Basso and Zhang (2007) and Wan et al. (2016), as shown in Figure 2.3, we adopt an infinite linear city model to derive shipper demand conditional on port service charges p_i and port adaptation investments I_i^a, I_i^t in response to disaster occurrence probability x. The value to the shipper of using the port service V is exogenous. Shippers have to choose which port to use before observing event of disaster occurrence or not.[17] The expected damage incurred

[17] Shippers are assumed to make their port choice decisions before observing the realization of disaster occurrence or not. If the disaster occurs, shippers cannot make the decisions to switch ports. This assumption is based on observations in (Magala and Sommons, 2008; Tongzon, 2009) that shippers/shipping lines often sign long-term contract with terminal operators. Ad hoc re-routing and rescheduling to other ports are difficult. Shippers/shipping lines could commit to particular ports/terminals due to integration and investment in hinterland transport,

on the shipper is $x\,\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\}$. D is the damage without any port adaptation when disaster occurs. $\eta(I_i^a + I_i^t)$ is the reduction of damage owing to port authority and terminal operator adaptation. [18] The disaster damage to shippers can include the cargo damage and inventory delay cost. If the disaster does not occur, shippers do not incur any cargo damage. With the disaster occurrence probability x, the expected damage incurred on shippers is $x\,\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\}$ [19].

Shippers are assumed to be uniformly distributed on the linear city with density 1. Shippers incur a cost of t per unit distance to transport cargo from its location to the port. This transport cost can also capture any horizontal differentiation (service homogeneity) of two ports' services perceived by the shippers. Shippers choose which port to use, and directly pay the terminal operator. The terminal operator pays port authority a concession fee in exchange to use the port land and basic infrastructure. The port charges within a port are determined in a "vertical structure": the port authority chooses its concession fee ϕ_i on the terminal operator first, and then the terminal operator chooses its service charge p_i on shippers. Table 2.1 summarizes notations and parameters definitions in our economic model.

warehousing and other forms of cooperation with port sector (Chang et al., 2008; Wiegmans et al., 2008; Franc and van der Horst, 2010).

[18] We assume the disaster imposes the damage cost on shippers. Port authorities and terminal operators can also have damage in their properties and equipment when disaster occurs. However, port authorities and terminal operators within and across the ports interact with each other through the shipper's demand, thus the specific damage to each entity does not enter the other entities' FOC. As a result, the specific damage to port authority/terminal operator only affects the magnitude of the adaptation investment, while not qualitatively affect the effects of Knightian uncertainty, and the inter-port/intra-port interactions on adaptations.

[19] This linear form of damage reduction by port adaptation is associated with the disasters forms such as the strong wind, rainfall and drought. The adaptations to these disasters can reduce damage to shippers in a proportion of the amount of the adaptation investment. Thus, a linear form of damage function in adaptation investments could be appropriate. Some types of disasters exhibit the all-or-nothing feature depending on whether the adaptation is above a threshold or not (for example, a dike to protect high wave). However, considering this step-wise damage function will dramatically complicate the model, and future studies may be called for.

Figure 2.3 Shipper's utility at each port after completion of adaptation investments

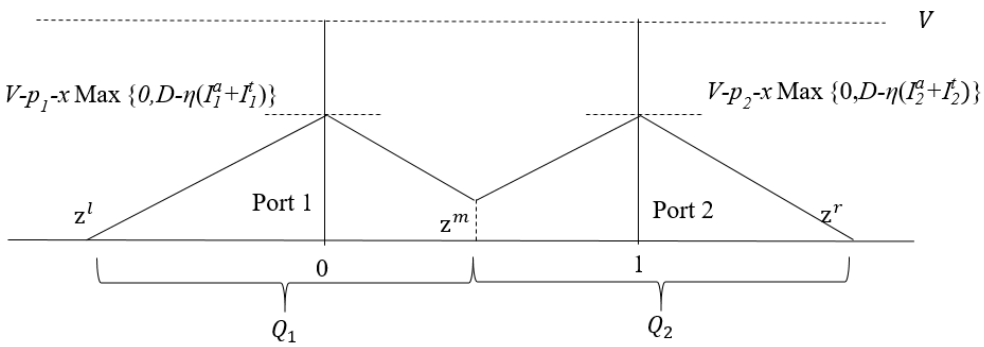


Table 2.1 Notational glossary

Parameter	Definition
V	Utility to shipper of using the port service
D	Level of disaster damage to the shipper, and we assume $D < V$
η	Effectiveness of adaptation investment to reduce damage
t	Unit distance transport cost for the shipper to move cargo to the port
I_i^a	Adaptation investment made by port authority at port i
I_i^t	Adaptation investment made by terminal operator at port i
x	Random variable denoting probability of the disaster occurrence
Ω	The expectation of x at adaptation investment stage
Σ	The variance of x at adaptation investment stage
Ψ	The second moment of x, which is equal to $\Omega^2 + \Sigma$
p_i	The service fee charged by terminal operator to shippers
ϕ_i	The concession fee charged by port authority to terminal operator
Q_i	The demand for service at port i at the operation stage
Π_i	Profit of terminal operator in port i at operation stage
π_i	Profit of port authority in port i at operation stage

For a shipper located at a point z in the two ports' common hinterland, the utility of using port 1 is $V - p_1 - zt - x\,\text{Max}\{0, D - \eta(I_1^a + I_1^t)\}$, and the utility of using port 2 is $V - p_2 - (1 - zt) - x\,\text{Max}\{0, D - \eta(I_2^a + I_2^t)\}$. For a shipper located at a point z in port 1's captive hinterland, the utility is $V - p_1 - |z|t - x\,\text{Max}\{0, D - \eta(I_1^a + I_1^t)\}$. For a shipper located at a point z in port 2's own hinterland, the utility is $V - p_2 - (z - 1)t - x\,\text{Max}\{0, D - \eta(I_2^a + I_2^t)\}$. We can then derive the marginal shipper's location z^l, who is indifferent between using port 1's service and not using the port service at all; the marginal shipper's location z^m, who is indifferent between using port 1 and using port 2's service; and the marginal shipper's location z^r, who is indifferent between using port 2's service and not using the port services. [20]

$$|z^l| = \frac{V - p_1 - x\,\text{Max}\{0, D - \eta(I_1^a + I_1^t)\}}{t} \tag{2.1.1}$$

$$z^r = 1 + \frac{V - p_2 - x\,\text{Max}\{0,\ D - \eta(I_2^a + I_2^t)\}}{t} \tag{2.1.2}$$

$$z^m = \frac{1}{2} + \frac{p_2 - p_1 - x\,\text{Max}\{0,\ D - \eta(I_1^a + I_1^t)\} + x\,\text{Max}\{0,\ D - \eta(I_2^a + I_2^t)\}}{2t} \tag{2.1.3}$$

The demand for each port at the operation stage is as follows:

$$Q_i(p)|(x, I^a, I^t) = \frac{1}{2} + \frac{2V + p_j - 3p_i + x\,\text{Max}\{0,\ D - \eta(I_j^a + I_j^t)\} - 3x\,\text{Max}\{0,\ D - \eta(I_i^a + I_i^t)\}}{2t} \tag{2.2}$$

The profits for terminal operators at operation stage is $\Pi_i|(x, I^a, I^t) = (p_i - \phi_i)Q_i$. Port authorities' profits at operation stage are $\pi_i|(x, I^a, I^t) = \phi_i Q_i$. For model tractability, we normalize operating cost of port authorities and terminal operators to be zero. At adaptation investment stage, terminal operators' expected profits are $E[\Pi_i] = [\int \Pi_i f(x)dx] - 0.5\omega {I_i^t}^2$. Port authorities' expected profits are $E[\pi_i] = [\int \pi_i f(x)dx] - 0.5\omega {I_i^a}^2$. At adaptation investment stage, port authorities incur adaptation investment cost $0.5\omega {I_i^a}^2$, and terminal operators incur $0.5\omega {I_i^t}^2$. The adaptation investment cost for both port authorities and terminal operators is assumed to be in quadratic form, indicating an increasing marginal cost of adaptation as technology requirement is higher and the

[20] For infinite decimals in all the formulas, two digits after the decimal points are reported in the chapter to save space.

overall difficulty increases to add more adaptation. ω is the adaptation cost parameter. Port authorities and terminal operators can have different adaptation measures. Port authorities' adaptations are mainly on port's basic infrastructure, such as building breakwaters, storm barriers, flood-control gates (Becker et al., 2012). These adaptations are not specific to protect particular terminals but to benefit entire port. Terminal operator's adaptation is mainly for its own berths and piers, e.g., the elevation of terminal, upgrading the drainage system, redesigning, and retrofitting of the terminal facilities (Becker et al., 2012). For model tractability and to focus on main insights, we assume port authorities and terminal operators to have the same adaptation investment cost structure, i.e., the same cost parameter ω. The consumer surplus for the shipper at the operation stage is as follows:

$$CS|(x, I^a, I^t) = \int_0^{|z^l|}[V - p_1 - x\,\mathrm{Max}\{0, D - \eta(I_1^a + I_1^t)\} - z\,t]\,dz + \int_0^{z^m}\ [V - p_1 - x\,\mathrm{Max}\{0, D - \eta(I_1^a + I_1^t)\} - z\,t]dz + \int_{z^m}^{1}[V - p_2 - x\,\mathrm{Max}\{0, D - \eta(I_2^a + I_2^t)\} - (1 - z)\,t]dz + \int_1^{z^r}[V - p_2 - x\,\mathrm{Max}\{0, D - \eta\,(I_2^a + I_2^t)\} - (z - 1)t]dz \tag{2.3}$$

The social welfare for the two-port system at operation stage is defined as $SW = CS + \sum_{i=1}^{2}\pi_i + \sum_{i=1}^{2}\Pi_i$.

2.3 Analysis

We adopt backward induction to solve the model. First, operation stage is analyzed on shipper port choice decision and pricing behavior of port authorities and terminal operators (Section 2.3.1). At operation stage, disaster occurrence probability x is realized, and port adaptation is also completed. Second, we analyze port adaptation decisions at adaptation investment stage, where disaster occurrence probability is ambiguous with a Knightian uncertainty (Section 2.3.2).

2.3.1 Port pricing

At port operation stage, adaptations I^a, I^t have been completed, and the disaster occurrence probability x is also realized. The port charges within a port are determined in a "vertical structure": the port authority decides on its concession fee to terminal operator first as the upstream, and then the terminal operator as downstream chooses its service charge to be paid by shippers. Terminal operators maximize profit by setting service charge p_i to shippers. They also pay concession fee ϕ_i to port authorities. The profit function of terminal operator is $\underset{p_i}{\text{Max}}\, \Pi_i\,|(x, I^a, I^t) = (p_i - \phi_i)Q_i$.

$$p_i(\phi_i, \phi_j) = 0.2\big[(2V + t) + 2.57\phi_i + 0.42\phi_j - 2.43x\,\text{Max}\{0,\ D - \eta(I_i^a + I_i^t)\}\big\} + 0.42\text{Max}\big\{0,\ D - \eta\big(I_j^a + I_j^t\big)\big\}] \tag{2.4}$$

It is noted that $p_i(\phi_i, \phi_j)$ is a function of two port authorities' concession fees ϕ_i and ϕ_j due to the interaction of two ports in the common hinterland. But ϕ_i has more impact on the port charge $p_i(\phi_i, \phi_j)$ at the same port. While terminal operators at two ports compete, port authorities may compete or cooperate (monopoly). Pricing rules of port authorities thus depend on inter-competition or cooperation (monopoly).

2.3.1.1 Pricing rule of competing port authorities

The objective of each competing port authority is $\underset{\phi_i}{\text{Max}}\, \pi_i|(x, I^a, I^t) = \phi_i Q_i(p_i(\phi_i, \phi_j), p_j(\phi_i, \phi_j))$. It is noted that π_i is a function of $p_i(\phi_i, \phi_j)$, and $p_j(\phi_i, \phi_j)$ because shippers directly pay terminal operators. Substituting $p_i(\phi_i, \phi_j)$ and $p_j(\phi_i, \phi_j)$ into π_i such that port authority has $\underset{\phi_i}{\text{Max}}\, \pi_i|(x, I^a, I^t) = \phi_i Q_i(\phi_i, \phi_j)$. Solving the first-order conditions (FOCs), $\frac{\partial \pi_i}{\partial \phi_i} = 0$ and $\frac{\partial \pi_j}{\partial \phi_j} = 0$, the optimal concession fee $\phi_i|(x, I^a, I^t)$ is as follows. The second-order conditions (SOCs), $\frac{\partial^2 \pi_i}{\partial {\phi_i}^2} < 0$ and $\frac{\partial^2 \pi_j}{\partial {\phi_j}^2} < 0$, are also satisfied.

$$\bar{\phi}_i|(x, I^a, I^t) = 0.23(2V + t) - x\left[0.50\,\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\} - 0.045\,\mathrm{Max}\{0, D - \eta\left(I_j^a + I_j^t\right)\}\right] \quad (2.5.1)$$

Inserting $\bar{\phi}_1\,|(x, I^a, I^t)$, and $\bar{\phi}_2\,|(x, I^a, I^t)$ to $p_1(\phi)$ and $p_2(\phi)$, and $Q_1\,(p)$ and $Q_2\,(p)$ we have:

$$\bar{p}_i = 0.34(2V + t) - x\left[0.74\,\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\} - 0.066\,\mathrm{Max}\{0, D - \eta\left(I_j^a + I_j^t\right)\}\right] \quad (2.5.2)$$

and

$$\bar{Q}_i = \frac{0.16\,(2V+t) - x\left[0.36\,\mathrm{Max}\{0,\ D - \eta(I_i^a + I_i^t)\} - 0.032\,\mathrm{Max}\left\{0, D - \eta\left(I_j^a + I_j^t\right)\right\}\right]}{t} \quad (2.5.3)$$

The following comparative statics are obtained to show the impact of adaptation investment and probability of disaster occurrence on port charges and port demands. Port authority and terminal operator charge more (less) and have more (less) demand if its own port (the other port) makes more adaptation. The disaster occurrence probability x, however, has two countervailing effects on port charges and demands. On one hand, higher disaster occurrence probability increases the expected damage cost for shippers, decreasing port's demand and charge ceteris paribus. On the other hand, with two ports competing in a common hinterland, if one port prevails over the other in adaptation (i.e., when $\frac{\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\}}{\mathrm{Max}\{0, D - \eta\left(I_j^a + I_j^t\right)\}} \leq 0.089$), higher disaster occurrence probability makes this much better adapted port more appealing to shippers, such that disaster occurrence probability has a positive effect on port charge and demand.

$$\frac{\partial \bar{\phi}_i}{\partial I_i^a} \geq 0;\ \frac{\partial \bar{\phi}_i}{\partial I_i^t} \geq 0;\ \frac{\partial \bar{\phi}_i}{\partial I_j^a} \leq 0;\ \frac{\partial \bar{\phi}_i}{\partial I_j^t} \leq 0$$

$$\frac{\partial \bar{\phi}_i}{\partial x} \leq 0 \text{ if } \frac{\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\}}{\mathrm{Max}\{0, D - \eta\left(I_j^a + I_j^t\right)\}} \geq 0.089;\ \frac{\partial \bar{\phi}_i}{\partial x} \geq 0 \text{ if } \frac{\mathrm{Max}\{0, D - \eta(I_i^a + I_i^t)\}}{\mathrm{Max}\{0, D - \eta\left(I_j^a + I_j^t\right)\}} \leq 0.089$$

$$\frac{\partial \bar{p}_i}{\partial I_i^a} \geq 0;\ \frac{\partial \bar{p}_i}{\partial I_i^t} \geq 0;\ \frac{\partial \bar{p}_i}{\partial I_j^a} \leq 0;\ \frac{\partial \bar{p}_i}{\partial I_j^t} \leq 0$$

$$\frac{\partial \bar{p}_i}{\partial x} \leq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \geq 0.089 \text{ ; } \frac{\partial \bar{p}_i}{\partial x} \geq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \leq 0.089$$

$$\frac{\partial \bar{Q}_i}{\partial I_i^a} \geq 0; \frac{\partial \bar{Q}_i}{\partial I_i^t} \geq 0; \frac{\partial \bar{Q}_i}{\partial I_j^a} \leq 0; \frac{\partial \bar{Q}_i}{\partial I_j^t} \leq 0$$

$$\frac{\partial \bar{Q}_i}{\partial x} \leq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \geq 0.089 \text{ ; } \frac{\partial \bar{Q}_i}{\partial x} \geq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \leq 0.089$$

2.3.1.2 Pricing rule of monopoly port authority

The monopoly port authority maximizes a joint profit at two ports as $\underset{\phi_i,\phi_j}{\text{Max}} \sum_{i=1}^{2} \pi_i \,|(x, I^a, I^t) = \sum_{i=1}^{2} \phi_i Q_i(\phi_i, \phi_j)$. FOCs are $\frac{\partial(\pi_i+\pi_j)}{\partial \phi_i} = 0$ and $\frac{\partial(\pi_i+\pi_j)}{\partial \phi_j} = 0$. SOCs $\frac{\partial^2(\pi_i+\pi_j}{\partial {\phi_i}^2} < 0$ and $\frac{\partial^2(\pi_i+\pi_j)}{\partial {\phi_j}^2} < 0$ are also satisfied. The optimal concession fees are $\tilde{\phi}_i|(x, I^a, I^t) = 0.25(2V+t) - 0.5x(\text{Max}\{0, D-\eta(I_i^a+I_i^t)\})$. Substituting $\tilde{\phi}_i\,|(x, I^a, I^t)$ into $p_i(\phi_i, \phi_j)$ and also $Q_i(\phi_i, \phi_j)$.

$$\tilde{p}_i = 0.35(2V+t) - x\left[0.74\,\text{Max}\{0,\ D-\eta(I_i^a+I_i^t)\} - 0.043\,\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}\right] \tag{2.6.1}$$

and

$$\tilde{Q}_i = \frac{0.15\,(2V+t) - x\left[0.36\,\text{Max}\{0,\ D-\eta(I_i^a+I_i^t)\} - 0.064\,\text{Max}\{0,\ D-\eta(I_j^a+I_j^t)\}\right]}{t} \tag{2.6.2}$$

Below are comparative statics of port charges and demands with respect to disaster occurrence probability and port adaptation investment. For monopoly port authority, it increases concession fee at one port when this port increases adaptation i.e., $\frac{\partial \tilde{\phi}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \tilde{\phi}_i}{\partial I_i^t} \geq 0$. In addition, with monopoly power, port authority can raise concession fee when disaster occurrence has higher probability i.e., $\frac{\partial \tilde{\phi}_i}{\partial x} \geq 0$. For terminal operator, it can charge more to shipper when its port adapts more i.e., $\frac{\partial \tilde{p}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \tilde{p}_i}{\partial I_i^t} \geq 0$, but charges less when the other port has more adaptation i.e., $\frac{\partial \tilde{p}_i}{\partial I_j^a} \leq$

0; $\frac{\partial \tilde{p}_i}{\partial I_j^t} \leq 0$. Similar to the competing port authorities case, the disaster occurrence probability has two countervailing effects on concession fee and terminal operators' charge. When $\frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} < 0.057$ holds, which means one port is much better adapted compared to the other port, disaster occurrence has overall positive effect such that port authority and terminal operator at one port can increase charge.

$$\frac{\partial \tilde{\phi}_i}{\partial x} \geq 0; \frac{\partial \tilde{\phi}_i}{\partial I_i^a} \geq 0; \frac{\partial \tilde{\phi}_i}{\partial I_i^t} \geq 0; \frac{\partial \tilde{\phi}_i}{\partial I_j^a} = 0; \frac{\partial \tilde{\phi}_i}{\partial I_j^t} = 0$$

$$\frac{\partial \tilde{\phi}_i}{\partial x} \leq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \geq 0.057; \frac{\partial \tilde{\phi}_i}{\partial x} > 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \leq 0.057$$

$$\frac{\partial \tilde{p}_i}{\partial I_i^a} \geq 0; \frac{\partial \tilde{p}_i}{\partial I_i^t} \geq 0; \frac{\partial \tilde{p}_i}{\partial I_j^a} \leq 0; \frac{\partial \tilde{p}_i}{\partial I_j^t} \leq 0$$

$$\frac{\partial \tilde{Q}_i}{\partial I_i^a} \geq 0; \frac{\partial \tilde{Q}_i}{\partial I_i^t} \geq 0; \frac{\partial \tilde{Q}_i}{\partial I_j^a} \leq 0; \frac{\partial \tilde{Q}_i}{\partial I_j^t} \leq 0$$

$$\frac{\partial \tilde{Q}_i}{\partial x} \leq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \geq 0.057 \text{ ; } \frac{\partial \tilde{Q}_i}{\partial x} \geq 0 \text{ if } \frac{\text{Max}\{0, D-\eta(I_i^a+I_i^t)\}}{\text{Max}\{0, D-\eta(I_j^a+I_j^t)\}} \leq 0.057$$

Port concession fees and terminal operator charges comparison is $\bar{\phi}_i < \tilde{\phi}_i$; $\bar{p}_i < \tilde{p}_i$ as shown below, which leads to our Lemma 2.1.

$$\tilde{\phi}_i - \bar{\phi}_i = 0.024 \times (2V + t) - x\big[0.0039\text{Max}\{0, D - \eta(I_i^a + I_i^t)\} + 0.044\text{Max}\big\{0, D - \eta\big(I_j^a + I_j^t\big)\big\}\big] > 0$$

$$\tilde{p}_i - \bar{p}_i = 0.015 \times (2V + t) - x\big[0.0058\text{Max}\{0, D - \eta(I_i^a + I_i^t)\} + 0.023\text{Max}\big\{0, D - \eta\big(I_j^a + I_j^t\big)\big\}\big] > 0$$

Lemma 2.1: *Conditional on disaster occurrence probability and the adaptation investment at two ports, inter-port competition between two port authorities leads to lower concession fee and lower terminal operator charge.*

This lemma holds for general functional form (as shown in Appendix A1), suggesting that monopoly price is higher than duopoly competition price. This is because, as concession fees at two ports are strategic complements, the monopoly port authority is able to internalize the externality of concession fee rise at one port on the other port. This leads to a higher concession fee and terminal operator charge at both ports.

In addition, our comparative statics demonstrate: $\frac{\partial \bar{\phi}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \bar{\phi}_i}{\partial I_i^t} \geq 0$; $\frac{\partial \bar{\phi}_i}{\partial I_j^a} \leq 0$; $\frac{\partial \bar{\phi}_i}{\partial I_j^t} \leq 0$; $\frac{\partial \bar{p}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \bar{p}_i}{\partial I_i^t} \geq 0$; $\frac{\partial \bar{p}_i}{\partial I_j^a} \leq 0$; $\frac{\partial \bar{p}_i}{\partial I_j^t} \leq 0$ and $\frac{\partial \tilde{\phi}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \tilde{\phi}_i}{\partial I_i^t} \geq 0$; $\frac{\partial \tilde{\phi}_i}{\partial I_j^a} = 0$; $\frac{\partial \tilde{\phi}_i}{\partial I_j^t} = 0$; $\frac{\partial \tilde{p}_i}{\partial I_i^a} \geq 0$; $\frac{\partial \tilde{p}_i}{\partial I_i^t} \geq 0$; $\frac{\partial \tilde{p}_i}{\partial I_j^a} \leq 0$; $\frac{\partial \tilde{p}_i}{\partial I_j^t} \leq 0$.

These lead to Lemma 2.2 about the impact of port adaptation on port charges.

Lemma 2.2: *For ports with competing port authorities, concession fee and terminal operator charge increase with own port's adaptation, but decrease with the other port's adaptation. For monopoly port authority, concession fee and terminal operator charge also increase with own port's adaptation, while not affected by the other port's adaptation.*

As shown in Figure A1 in Appendix A1, for competing port authorities, when one port increases adaptation (e.g., port i), the best response function of port j's concession fee $\phi_j(\phi_i)$ moves outward due to stronger competing pressure from port i. The best response function of port i's concession fee $\phi_i(\phi_j)$ moves downward. Thus, at new equilibrium, concession fee rises at the port with an increased adaptation (port i), while the concession fee at the other port (port j) decreases. When one port increases adaptation, terminal operator at this port thus has to pay a higher concession fee and also has larger shipper demand, both imposing positive effects on the terminal operator charge. When the other port increases adaptation, terminal operator at one port faces lower concession fee and also lower shipper demand, thus making it to reduce charge to shipper.

For monopoly port authority, when adaptation at one port increases, port authority rises concession fee at this port. Meanwhile, it can internalize the positive externality of concession fee rise on the

other port by not reducing the other port's concession fee. For terminal operator, the impact of adaptation change on its charge is the same. When one port increases adaptation, terminal operator at this port pays higher concession fee while also having larger shipper demand, both having positive effects on its charge. When the other port increases adaptation, terminal operator at one port pays a lower concession fee with lower shipper demand, making it to lower charge to shipper.

Taking derivatives of the difference in concession fees and terminal operator charges with respect to adaptation investments, we can see $\frac{\partial(\tilde{\phi}_i|(x,I^a,I^t)-\bar{\phi}_i|(x,I^a,I^t))}{\partial I} > 0$; $\frac{\partial(\tilde{p}_i|(x,I^a,I^t)-\bar{p}_i|(x,I^a,I^t))}{\partial I} > 0$, where $I \in \{I_i^a, I_i^t, I_j^a, I_j^t\}$.

Proposition 2.1: *Increased port adaptation at either port would enlarge the differences in both concession fee and terminal operator charge between the competing and cooperative ports.*

Detailed explanation of Proposition 2.1 is as follows. With adaptation increased at one port, monopoly port authority internalizes the externality to the other port, thus making the concession fee to rise more than that with the competing port authorities. Terminal operator charge increases with concession fee, such that its charge increases with monopoly port authority. Therefore, the difference in concession fee and terminal charge between competing and monopoly port authority is enlarged. On the other hand, when the other port increases adaptation, the monopoly port authority does not change the concession fee at one port, whereas the competing port authorities would reduce concession fee in response. Thus, the difference in concession fee and terminal charge at one port is also enlarged when the other port increases adaptation.

2.3.2 Adaptation investment

At adaptation investment stage, disaster occurrence probability x has not been realized and has a Knightian uncertainty. Specifically, x is a random variable with a pdf $f(x)$, expectation Ω, variance Σ, and the second moment $\Psi = Ex^2 = \Omega^2 + \Sigma$. Next, analogous to operation stage analyses, we discuss different inter-and intra- port competition and cooperation regimes. Port authorities and terminal operations are assumed to simultaneously make adaptation investment

decisions. This is because adaptation projects are lengthy, such that each party makes adaptation decision well in-advance, while only observing completed adaptations by the others after a long-period.

2.3.2.1 Adaptation of competing port authorities

The pricing rule follows that of two competing port authorities at operation stage i.e. $\bar{\phi}_i$ and $\bar{p}_i$. The expected profits for port authorities at adaptation investment stage are:

$$E[\pi_i] = [\int \pi_i f(x)dx] - 0.5\omega I_i^{a\,2} = 0.15\frac{V^2}{t} + 0.15V + 0.037t + \frac{1}{t}\left\{\begin{matrix} 0.15\begin{bmatrix}1.1\,\mathrm{Max}\{0,\ D-\eta(I_i^a+I_i^t)\}-\\ 0.1\,\mathrm{Max}\{0,\ D-\eta\left(I_j^a+I_j^t\right)\}\end{bmatrix}^2\Psi \\ -0.30\Omega(V+0.50t)\begin{bmatrix}1.10\,\mathrm{Max}\{0,\ D-\eta(I_i^a+I_i^t)\}-\\ 0.10\,\mathrm{Max}\{0,\ D-\eta\left(I_j^a+I_j^t\right)\}\end{bmatrix}\end{matrix}\right\} - 0.5\omega I_i^{a\,2} \tag{2.7.1}$$

The expected profits for terminal operators are:

$$E[\Pi_i] = [\int \Pi_i f(x)dx] - 0.50\omega I_i^{t\,2} = 0.072\frac{V^2}{t} + 0.072V + 0.018t + \frac{1}{t}\left\{\begin{matrix} 0.072\begin{bmatrix}1.10\,\mathrm{Max}\{0,\ D-\eta(I_i^a+I_i^t)\}-\\ 0.10\,\mathrm{Max}\{0,\ D-\eta\left(I_j^a+I_j^t\right)\}\end{bmatrix}^2\Psi - \\ 0.14\,\Omega\,(V+0.5t)\begin{bmatrix}1.10\,\mathrm{Max}\{0,\ D-\eta(I_i^a+I_i^t)\}-\\ 0.10\,\mathrm{Max}\{0,\ D-\eta\left(I_j^a+I_j^t\right)\}\end{bmatrix}\end{matrix}\right\} - 0.5\omega I_i^{t\,2} \tag{2.7.2}$$

Port authorities and terminal operators maximize expected profits respectively. The constraints $\eta(I_i^a + I_i^t) \leq D$ must be imposed in the sense that ports choose not to adapt beyond the total possible level of disaster damage D: $\underset{I_i^a}{\mathrm{Max}}\,\mathrm{E}[\pi_i]$, st. $\eta(I_i^a + I_i^t) \leq D$; $\underset{I_i^t}{\mathrm{Max}}\,\mathrm{E}[\Pi_i]$, st. $\eta(I_i^a + I_i^t) \leq D$.

To solve above constrained optimization problem, we first assume the constraints are not binding at equilibrium, and then discuss conditions to reach such interior solutions. For port authorities, FOCs with respect to I_i^a are as follows:

$$\frac{\partial E[\pi_i]}{\partial I_i^a} = 0.33\frac{\eta}{t}\,[(V+0.50t)\Omega - D\Psi] - 0.032\,\frac{\eta^2}{t}\Psi\left(I_j^a + I_j^t\right) + 0.36\,\frac{\eta^2}{t}\Psi I_i^t + \left(0.36\,\frac{\eta^2}{t}\Psi - \omega\right)I_i^a \tag{2.7.3}$$

The SOCs require $\omega \geq 0.36\,\frac{\eta^2}{t}\Psi$. This is to guarantee that port authorities' expected profits are concave in I_i^a. If $\omega < 0.36\,\frac{\eta^2}{t}\Psi$, port authorities' expected profit functions are convex in I_i^a such that marginal return of adaptation investment always increases, suggesting port authority to keep investing till reaching the bound $\eta(I_i^a + I_i^t) = D$. FOCs for terminal operators are as follows:

$$\frac{\partial E[\Pi_i]}{\partial I_i^t} = 0.16\frac{\eta}{t}\,[(V+0.50t)\Omega - D\Psi] - 0.015\,\frac{\eta^2}{t}\Psi\left(I_j^a + I_j^t\right) + 0.17\,\frac{\eta^2}{t}\Psi I_i^a + (0.17\,\frac{\eta^2}{t}\Psi - \omega)I_i^t \tag{2.7.4}$$

SOCs require $\omega \geq 0.17\,\frac{\eta^2}{t}\Psi$ so that terminal operators' expected profit functions are concave in I_i^t. If $\omega < 0.17\,\frac{\eta^2}{t}\Psi$, marginal return of adaptation investment for terminal operators always increases, such that they keep investing till reaching the bound $\eta(I_i^a + I_i^t) = D$.

The second derivatives indicate $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} \geq 0$; $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a} \leq 0$; $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t} \leq 0$, and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_i^t} \geq 0$; $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_j^a} \leq 0$; $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_j^t} \leq 0$. Thus, adaptation of port authority and terminal operator at the same port is strategic complement, while adaptation across ports is strategic substitute. In Appendix A2, we plot best response functions of adaptation I_i^a and I_i^t at the same port, and I_i^a and I_j^a at two different ports. The best response functions of I_i^a and I_i^t are positively sloped while those of I_i^a and I_j^a are negatively sloped. Solving the system equations of FOCs, and imposing symmetry, we obtain following symmetric interior equilibrium adaptation investments with competing port authorities.

$$\bar{I}_i^a = \bar{I}_j^a = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{6.1\,\omega t - 3\Psi\eta^2} \geq \bar{I}_i^t = \bar{I}_j^t = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{2.1\,(6.1\,\omega t - 3\,\Psi\eta^2)} \tag{2.7.5}$$

To have finite adaptation investment implies $\omega > 0.49\frac{\eta^2}{t}\Psi$, which to make the denominator to be positive. Existence of interior solution requires $\omega \geq \frac{0.48\,\Omega(V+0.50t)\eta^2}{Dt}$. It is noted that when constraint $\eta(I_i^a + I_i^t) \leq D$ binds at equilibrium, i.e., $\eta(I_i^a + I_i^t) = D$, there would be an infinite number of Nash equilibria of adaptation investment (see Appendix A2 for discussion). This happens when $\omega \leq \frac{0.48\,\Omega(V+0.50t)\eta^2}{Dt}$ such that adaptation is not costly enough, such that ports adapt as much as possible to achieve a "full insurance". This case of infinite Nash equilibria with binding constraint makes comparison between $\bar{I}_i^a$ and $\bar{I}_i^t$ and other implications of Knightian uncertainty unclear. In addition, in practice, port adaptation is likely to be extremely costly (OECD, 2016) and as a result, ports seldom fully adapt to a potential disaster (see survey in Becker et al. (2012)). Therefore, to simplify our discussion and to reflect real practice, we exclude discussion on the multiple equilibria under binding constraint. Taking total derivatives of the FOCs ($\frac{\partial E[\pi_i]}{\partial I_i^a} = 0$ and $\frac{\partial E[\Pi_i]}{\partial I_i^t} = 0$) to Ω and Σ respectively, and imposing the symmetry assumption, the expressions of $\frac{\partial \bar{I}_i^a}{\partial \Omega}$, $\frac{\partial \bar{I}_i^t}{\partial \Omega}$ and $\frac{\partial \bar{I}_i^a}{\partial \Sigma}$, $\frac{\partial \bar{I}_i^t}{\partial \Sigma}$ are shown in Appendix A3:

$$\frac{\partial \bar{I}_i^a}{\partial \Omega} \geq 0\,;\ \frac{\partial \bar{I}_i^t}{\partial \Omega} \geq 0\,;\ \frac{\partial \bar{I}_i^a}{\partial \Sigma} \leq 0\,;\ \frac{\partial \bar{I}_i^t}{\partial \Sigma} \leq 0$$

Proof of the above comparative statics is in Appendix A3. The sign of $\frac{\partial \bar{I}_i^a}{\partial \Omega}$ and $\frac{\partial \bar{I}_i^t}{\partial \Omega}$ is determined by $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$. As a higher expectation of disaster occurrence probability increases the marginal expected profit of port authority and terminal operator to their own adaptation, i.e., $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} \geq 0$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$, the equilibrium port adaptation also increases with the expectation of disaster occurrence probability, i.e., $\frac{\partial \bar{I}_i^a}{\partial \Omega} \geq 0$ and $\frac{\partial \bar{I}_i^t}{\partial \Omega} \geq 0$. In addition, the sign of $\frac{\partial \bar{I}_i^a}{\partial \Sigma}$ and $\frac{\partial \bar{I}_i^t}{\partial \Sigma}$ is determined by $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$. As larger variance of disaster occurrence probability decreases

the marginal expected profit of port authority and terminal operator to their own adaptation, the equilibrium port adaptation decreases with the variance of disaster occurrence probability as a result, i.e., $\frac{\partial \bar{I}_i^a}{\partial \Sigma} \leq 0$ and $\frac{\partial \bar{I}_i^t}{\partial \Sigma} \leq 0$.

2.3.2.2 Adaptation of monopoly port authority

The pricing rule at operation stage follows that of monopoly authority regime, i.e., $\tilde{\phi}_i$ and $\tilde{p}_i$. For monopoly port authority, the expected joint profit is as follows:

$$E[\pi_i + \pi_j] = [\int (\pi_i + \pi_j) f(x) dx] - 0.50\omega(I_i^{a\,2} + I_j^{a\,2}) = 0.30\frac{V^2}{t} + 0.30V + 0.15 - \frac{0.075}{t} + \frac{1}{t}\begin{bmatrix} 0.18\,(\text{Max}\{0, D - \eta(I_i^a + I_i^t)\})^2 \\ -0.064\ \text{Max}\{0, D - \eta(I_i^a + I_i^t)\} \\ \text{Max}\{0, D - \eta(I_j^a + I_j^t)\} + 0.18\,(\text{Max}\{0, D - \eta(I_j^a + I_j^t)\})^2 \end{bmatrix}\Psi - \Big(0.15 + 0.45\frac{V}{t}\Big)\Omega\big[\,\text{Max}\{0, D - \eta(I_i^a + I_i^t)\} + \text{Max}\{0, D - \eta(I_j^a + I_j^t)\}\big] - 0.50\omega\big(I_i^{a\,2} + I_j^{a\,2}\big) \tag{2.8.1}$$

Monopoly port authority maximizes the expected joint profit by choosing adaptation at two ports together: $\underset{I_i^a, I_j^a}{\text{Max}}\, E[\pi_i + \pi_j]$, st. $\eta(I_i^a + I_i^t) \leq D$ and $\eta(I_j^a + I_j^t) \leq D$. FOCs for the monopoly port authority are as follows. SOCs require that $\omega \geq 0.36\,\frac{\eta^2}{t}\Psi$.

$$\frac{\partial E[\pi_i + \pi_j]}{\partial I_i^a} = 0.30\frac{\eta}{t}\,[(V + 0.50t)\Omega - D\Psi] - 0.064\,\frac{\eta^2}{t}\Psi\big(I_j^a + I_j^t\big) + 0.36\,\frac{\eta^2}{t}\Psi I_i^t + (0.36\,\frac{\eta^2}{t}\Psi - \omega)I_i^a \tag{2.8.2}$$

Terminal operators maximize their expected profit as $\underset{I_i^t}{\text{Max}}\,\text{E}[\Pi_i]$; s.t. $\eta\,(I_i^a + I_i^t) \leq D$. FOCs are as follows. The SOCs require $\omega \geq 0.18\,\frac{\eta^2}{t}\Psi$.

$$\frac{\partial\, E[\Pi_i]}{\partial I_i^t} = 0.15\frac{\eta}{t}\,[(V+0.5t)\Omega - D\Psi] - 0.031\,\frac{\eta^2}{t}\Psi\left(I_j^a + I_j^t\right) + 0.18\,\frac{\eta^2}{t}\Psi I_i^a - (\omega - 0.18\,\frac{\eta^2}{t}\Psi)I_i^t \tag{2.8.3}$$

The second derivatives show $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t} \geq 0$; $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a} \leq 0$; $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t} \leq 0$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_i^t} \geq 0$; $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_j^a} \leq 0$; $\frac{\partial^2 E[\Pi_i]}{\partial I_i^a \partial I_j^t} \leq 0$. The adaptations of port authority and terminal operators within the same port are thus strategic complements, while adaptations across ports are strategic substitutes. Solving the system equations of FOCs for symmetric interior Nash equilibrium, following solution is obtained.

$$\tilde{I}_i^{\,a} = \tilde{I}_j^{\,a} = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.70\omega t - 3\Psi\eta^2} \geq \tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6\Psi\eta^2} \tag{2.8.4}$$

To make sure a finite adaptation investment requires $\omega > 0.45\,\frac{\eta^2}{t}\Psi$, while the interior solution requires $\omega \geq \frac{0.22\,\Omega(V+0.5t)\eta^2}{Dt}$. Taking total derivative of the FOCs ($\frac{\partial E[\pi_i+\pi_j]}{\partial I_i^a} = 0$ and $\frac{\partial\, E[\Pi_i]}{\partial I_i^t} = 0$) to Ω and Σ respectively, and imposing the symmetry assumption, $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega}$, $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega}$ and $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma}$ are shown in Appendix A3:

$$\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} \geq 0\,;\ \frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega} \geq 0\,;\ \frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma} \leq 0\ \ ;\ \frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma} \leq 0$$

Proof of the above comparative statics is also in Appendix A3. The sign of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega}$ and $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega}$ depends on $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}$. $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} \geq 0$ and $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega} \geq 0$, as $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$ and $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega} \geq 0$. That is, as a higher expectation of disaster occurrence probability increases the marginal expected profit of terminal operator, and marginal joint expected profit of the monopoly port authority to own adaptation, the equilibrium adaptation increases as a result. The sign of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma}$ depends on $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$. $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma} \leq 0$ and $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma} \leq 0$, as $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma} \leq 0$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$. That is, as larger variance of disaster occurrence probability decreases the marginal expected profit of terminal operator, and marginal

expected joint profit of the monopoly port authority to own adaptation, the equilibrium port adaptation decreases as a result.

2.3.2.3 Adaptation of competing port authorities with intra-port coordination

In this regime, port authorities compete with each other, but they can coordinate with terminal operators at each port on adaptation decision. Pricing rule at operation stage follows that of competing port authorities i.e. $\bar{\phi}_i$ and $\bar{p}_i$. Port authority and terminal operator at the same port now jointly maximize a total expected profit at one port: $\underset{I_i^a, I_i^t}{\text{Max}}\, E[\pi_i + \Pi_i]$, s.t. $\eta(I_i^a + I_i^t) \leq D$. FOCs for this intra-port coordination problem are as follows. SOCs require $\omega \geq 0.53\frac{\eta^2}{t}\Psi$.

$$\frac{\partial E[\pi_i+\Pi_i]}{\partial I_i^a} = \frac{\partial E[\pi_i+\Pi_i]}{\partial I_i^t} = 0.48\frac{\eta}{t}\,[(V+0.50t)\Omega - D\Psi] - 0.048\,\frac{\eta^2}{t}\Psi\left(I_j^a + I_j^t\right) + 0.53\,\frac{\eta^2}{t}\Psi\, I_i^t + (0.53\,\frac{\eta^2}{t}\Psi - \omega)I_i^a \tag{2.9.1}$$

The second derivatives show $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t} \geq 0$; $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a} \leq 0$; $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t} \leq 0$ .The adaptation investment of port authority and terminal operator at the same port is strategic complement, while adaptation investment across ports is strategic substitute. Solving the system equations of above FOCs, symmetric interior Nash equilibrium is obtained as follows:

$$\hat{I}_i^{\,a} = \hat{I}_j^{\,a} = \hat{I}_i^{\,t} = \hat{I}_j^{\,t} = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{4.1\,\omega t - 4\,\Psi\eta^2} \tag{2.9.2}$$

To make sure finite adaptation investment requires $\omega > 0.98\,\frac{\eta^2}{t}\Psi$. The interior Nash equilibrium requires $\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$. The derivatives of $\hat{I}_i^{\,a}$ and $\hat{I}_i^{\,t}$ to Ω is as follows.

Taking total derivative of the FOCs ($\frac{\partial E[\pi_i+\Pi_i]}{\partial I_i^a} = 0$ and $\frac{\partial E[\pi_i+\Pi_i]}{\partial I_i^t} = 0$) to Ω and Σ respectively, and imposing the symmetry assumption, $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega}$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega}$ and $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma}$ can be obtained as shown Appendix A3:

$$\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} \geq 0 \;\; ; \frac{\partial \hat{I}_i^{\,t}}{\partial \Omega} \leq 0 \; ; \frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma} \geq 0 \; ; \frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma} \leq 0$$

Proof of the above comparative statics is also in Appendix A3. The sign of $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega}$ and $\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega}$ depends on $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega}$. $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} \geq 0$ and $\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega} \geq 0$, as $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} \geq 0$ and $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$. That is, as a higher expectation of disaster occurrence probability increases the marginal expected joint profit of port authority and terminal operator at one port to their own adaptation, the equilibrium adaptation thus increases. The sign of $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma}$ depends on $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma}$. $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma} \leq 0$ and $\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma} \leq 0$, as $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} \leq 0$ and $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$. That is, as a larger variance of disaster occurrence probability decreases the marginal expected joint profit of port authority and terminal operator to their own adaptation at one port, the equilibrium port adaptation decreases as a result.

Table 2.2 summarizes the interior equilibrium adaptation, SOCs, finite adaptation investment condition and condition of interior equilibrium adaptation for the three regimes discussed above. The comparative statics of equilibrium adaptation to the expectation and variance of the disaster occurrence probability are as follows. Proposition 2.2. is obtained on the impact of Knightian uncertainty on port adaptation.

$$\frac{\partial \bar{I}_i^{\,a}}{\partial\, \Omega} \geq 0; \frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} \geq 0 \; ; \; \frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} \geq 0 \text{ and } \frac{\partial \bar{I}_i^{\,a}}{\partial \Sigma} \leq 0; \frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma} \leq 0 \; ; \frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma} \leq 0$$

$$\frac{\partial \bar{I}_i^{\,t}}{\partial\, \Omega} \geq 0; \frac{\partial \tilde{I}_i^{\,t}}{\partial \Omega} \geq 0 \; ; \; \frac{\partial \hat{I}_i^{\,t}}{\partial \Omega} \geq 0 \text{ and } \frac{\partial \bar{I}_i^{\,t}}{\partial \Sigma} \leq 0; \frac{\partial \tilde{I}_i^{\,t}}{\partial \Sigma} \leq 0 \; ; \frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma} \leq 0$$

Proposition 2.2: *Higher expectation of disaster occurrence probability increases adaptation, while larger variance of disaster occurrence probability reduces adaptation.*

Table 2.2 The summary of the Nash equilibrium of different inter-port competition and intra-port coordination regimes

Regimes	**Port authority adaptation**	**Terminal operator adaptation**	**SOCs and finite adaptation**	**Interior solution requirement**
Competing Port Authorities	$\bar{I}_i^a = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{6.1\omega t - 3\Psi\eta^2}$	$\bar{I}_i^t = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{2.1\,(6.1\,\omega t - 3\,\Psi\eta^2)}$	$\omega \geq 0.49\,\frac{\eta^2}{t}\Psi$	$\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$
Monopoly Port Authority	$\tilde{I}_i^a = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\,\Psi\eta^2}$	$\tilde{I}_i^t = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{13.7\,\omega t - 6.1\,\Psi\eta^2}$	$\omega \geq 0.45\,\frac{\eta^2}{t}\Psi$	$\omega \geq \frac{044\,\Omega(V+0.5t)\eta^2}{Dt}$
Competing Port Authorities with Intra-port Coordination	$\hat{I}_i^a = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{4.1\omega t - 4\,\Psi\eta^2}$	$\hat{I}_i^t = \frac{\eta\,[(2V+t)\,\Omega - 2D\Psi]}{4.1\omega t - 4\,\Psi\eta^2}$	$\omega \geq 0.98\,\frac{\eta^2}{t}\Psi$	$\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$

This analytical result may provide a sound explanation for why in practice port adaptation is much more difficult to implement than "mitigation", because our present knowledge about climate change and related disasters is far from reasonable accuracy. For example, Becker et al. (2012) and Ng et al. (2016) find that most surveyed ports cite the "inadequate information" and need to know more about the issue as a major reason for slow development of adaptation. On the other hand, the relatively low probability of the climate change related disaster also discourages the port's motivation to adapt. This is exemplified by Gulfport's (Mississippi US) decision to exclusively use the post-Katrina grant ($ 570 million) allocated by federal government to expand capacity, while canceling terminal elevation project to help protect against another Katrina-like hurricane. Although not severely affected by the most recent Hurricanes Harvey and Irma in August 2017, this port has been alerted that disaster occurrence probability may not be as low as it once perceived. The increase in expectation or risk of disaster occurrence probability stimulates adaptation investment. Ng et al. (2016) survey 21 Canadian ports' adaptation and find that ports subject to higher climate change risk adapt more. Our Proposition 2.2 is also consistent with existing economics and decision science literature. Camerer and Weber (1992) model a subjective expected utility (SEU) with Knightian uncertainty on event occurrence probability. They find people prefer to bet on events they know more about, even when their beliefs are held constant as

people are averse to ambiguity about the probability. Nishimura and Ozai (2007) investigate the effect of "Knightian uncertainty" on project investment decisions. It is found that ambiguity of Knightian uncertainty decreases the value of irreversible investment while the increase in risk increases it. The ranking of adaptation is $\hat{I}_i^a \geq \bar{I}_i^a \geq \tilde{I}_i^a$, which is because:

$$\hat{I}_i^a - \bar{I}_i^a = \frac{0.079\times\eta(2V\Omega-2D\Psi+\Omega t)(\omega t+0.51\Psi\eta^2)}{(\omega t-0.97\Psi\eta^2)(\omega t-0.48\Psi\eta^2)} > 0;\ \bar{I}_i^a - \tilde{I}_i^a = \frac{0.0132\times\eta(2V\Omega-2D\Psi+\Omega t)\omega t}{(\omega t-0.48\Psi\eta^2)(\omega t-0.45\Psi\eta^2)} > 0$$

Analogously, one can show $\hat{I}_i^t \geq \bar{I}_i^t \geq \tilde{I}_i^t$.

Proposition 2.3: *Port authorities' competition leads to higher adaptation (the competition effect), i.e.,* $\bar{I}_i^a \geq \tilde{I}_i^a$; $\bar{I}_i^t \geq \tilde{I}_i^t$. *Intra-port coordination between port authority and terminal operator at each port also increases adaptation i.e.,* $\hat{I}_i^a \geq \bar{I}_i^a$; $\hat{I}_i^t \geq \bar{I}_i^t$. *Thus, without intra-port coordination, port authority and terminal operator at the same port "free-ride" on each other adaptation by investing in less adaptation (the free-riding effect).*

Adaptation across ports is strategic substitute such that an increase in one port's adaptation imposes negative externality on the other port's expected profit. When two ports are controlled by a monopoly port authority, they coordinate to internalize such negative externality through reducing adaptation investment at two ports. Thus, inter-port competition between private terminal operators increase port adaptation investments of two ports (the competition effect). On the other hand, port authorities' adaptation and terminal operator's adaptation within one port is strategic complement such that an increase in adaptation by one party benefits the other. As a result, port authority and terminal operator free-ride on each other with a less incentive to adapt (the free-riding effect).

The ratio of the adaptation between competing port authorities and monopoly port authority is $\frac{\bar{I}_i^a}{\hat{I}_i^a} = 1.09 \times \frac{(\omega t-0.45\Psi\eta^2)}{(\omega t-0.49\Psi\eta^2)}$, which measures the degree of the competition effect. $\frac{\partial}{\partial\Omega}\left(\frac{\bar{I}_i^a}{\hat{I}_i^a}\right) = \frac{0.085\,\Omega\eta^2\omega t}{(\omega t-0.49\Psi\eta^2)^2} > 0$; $\frac{\partial}{\partial\Sigma}\left(\frac{\bar{I}_i^a}{\hat{I}_i^a}\right) = \frac{0.042\,\Omega\eta^2\omega t}{(\omega t-0.485\Psi\eta^2)^2} > 0$. Analogously, $\frac{\partial}{\partial\Omega}\left(\frac{\bar{I}_i^t}{\hat{I}_i^t}\right) > 0$, $\frac{\partial}{\partial\Sigma}\left(\frac{\bar{I}_i^t}{\hat{I}_i^t}\right) > 0$. The ratio of the adaptation between intra-port coordination and no coordination for competing port

authorities is $\frac{\hat{I}_i^a}{\bar{I}_i^a} = 1.49 \times \frac{(\omega t - 0.49\Psi\eta^2)}{(\omega t - 0.97\Psi\eta^2)}$, which measures the degree of the free-riding effect. $\frac{\partial}{\partial\Omega}\left(\frac{\hat{I}_i^a}{\bar{I}_i^a}\right) = \frac{1.44\,\Omega\eta^2\omega t}{(\omega t - 0.97\Psi\eta^2)^2} > 0$; $\frac{\partial}{\partial\Sigma}\left(\frac{\hat{I}_i^a}{\bar{I}_i^a}\right) = \frac{0.72\,\Omega\eta^2\omega t}{(\omega t - 0.97\Psi\eta^2)^2} > 0$. Analogously, it can be proved that $\frac{\partial}{\partial\Omega}\left(\frac{\hat{I}_i^t}{\bar{I}_i^t}\right) > 0$; $\frac{\partial}{\partial\Sigma}\left(\frac{\hat{I}_i^t}{\bar{I}_i^t}\right) > 0$.

Proposition 2.4: *Higher expectation and larger variance of disaster occurrence strengthen both the competition effect and the free-riding effect.*

Proposition 2.4 suggests that a higher expectation and larger variance of disaster occurrence probability enhance the competition effect and the free-riding effect. For the competition effect, when two port authorities compete on adaptation, if the expectation of disaster occurrence probability increases, they have a stronger incentive to adapt compared to the monopoly port authority, strengthening the competition effect. When the variance of disaster occurrence probability increases, as suggested by Proposition 2.2, two ports reduce adaptation investment. However, when port authorities compete, they reduce adaptation less compared to that of monopoly port authority. As a result, an increased variance of disaster occurrence probability also enlarges difference in adaptation for competing port authorities and monopoly port authority, enhancing the competition effect. For the free-riding effect, when the expectation of disaster occurrence probability increases, the marginal expected profit of adaptation investment is larger, such that one party (port authority or terminal operator) benefits more from the other party's adaptation, thus enhancing the free-riding incentive. When the variance of disaster occurrence probability increases, each party reduces adaptation. Without coordination, such reduction is more significant, thus also enlarging the difference with and without intra-port coordination. This strengthens the free-riding effect.

Last, we investigate the implications of inter-port competition and intra-port cooperation on the expected social welfare of the two-port system. $E[\overline{SW}]$ is the expected social welfare with competing port authorities; $E[\widetilde{SW}]$ is the expected social welfare with monopoly port authority; $E[\widehat{SW}]$ is the expected social welfare with competing port authorities and with intra-port coordination. The expression of $E[\widehat{SW}] - E[\overline{SW}]$ is as below.

$$E[\widehat{SW}] - E[\overline{SW}] = \frac{0.048\omega(t^2\omega^2 - 0.96\Psi\eta^2 t\omega + 0.068\Psi^2\eta^2)\eta^2(2\Omega V - 2D\Psi + \Omega t)^2}{(\omega t - 0.49\Psi\eta^2)^2(\omega t - 0.97\Psi\eta^2)^2} > 0$$

The sign of $E[\widehat{SW}] - E[\overline{SW}]$ is determined by the term $t^2\omega^2 - 0.96\Psi\eta^2 t\omega + 0.068\Psi^2\eta^2$ in the numerator, which is a convex quadratic function of ω. The two solutions of $t^2\omega^2 - 0.96\Psi\eta^2 t\omega + 0.068\Psi^2\eta^2 = 0$ are $0.096\ \frac{\eta^2}{t}\Psi$ and $0.86\ \frac{\eta^2}{t}\Psi$. The finite adaptation investment condition for $\hat{I}_i^a$ and $\hat{I}_i^t$ suggests $\omega > 0.98\frac{\eta^2}{t}\Psi$, such that $t^2\omega^2 - 0.96\Psi\eta^2 t\omega + 0.068\Psi^2\eta^2 > 0$. Thus $E[\widehat{SW}] - E[\overline{SW}] > 0$. The expression of $E[\overline{SW}] - E[\widetilde{SW}]$ is as below, which is apparently positive.

$$E[\overline{SW}] - E[\widetilde{SW}] = \frac{0.0056 \times \omega^2\eta^2 t(2\Omega V - 2D\Psi + \Omega t)^2(\omega t - 0.47\Psi\eta^2)}{(\omega t - 0.445\Psi\eta^2)^2(\omega t - 0.49\Psi\eta^2)^2} > 0$$

The ranking of expected social welfare is $E[\widehat{SW}] > E[\overline{SW}] > E[\widetilde{SW}]$.

Proposition 2.5: *The expected social welfare increases with the port adaptation. Intra-port coordination between port authorities and terminal operators results in the highest expected social welfare by overcoming the free-riding effect. Monopoly port authority, on the contrary, leads to the smallest expected social welfare with the lowest level of port adaptation.*

Proposition 2.5 may have several policy implications. First, from the social welfare perspective, with uncertain natural disaster threat, it is better to have ports controlled by different port authorities. Inter-port competition between port authorities results in more adaptation, and higher expected total social welfare. Regulators should avoid granting monopoly power to a single port authority in a multiple-port region. Second, intra-port coordination on adaptation between port authority and terminal operator should be encouraged to address the free-riding effect on adaptation. Unlike anti-trust concern on pricing collision, regulators should allow and even facilitate intra-port coordination between port authority and terminal operator to jointly plan port adaptation. When the revenue-sharing mechanism can be figured out between port authority and terminal operator, they have incentive to coordinate adaptation as the total expected profit is

maximized. The experience of the port of San Diego [21] can be learnt by more ports to better develop framework and mechanism to involve terminal operators to discuss, plan and implement port adaptation.

2.4 Effects of Port Competition Intensity

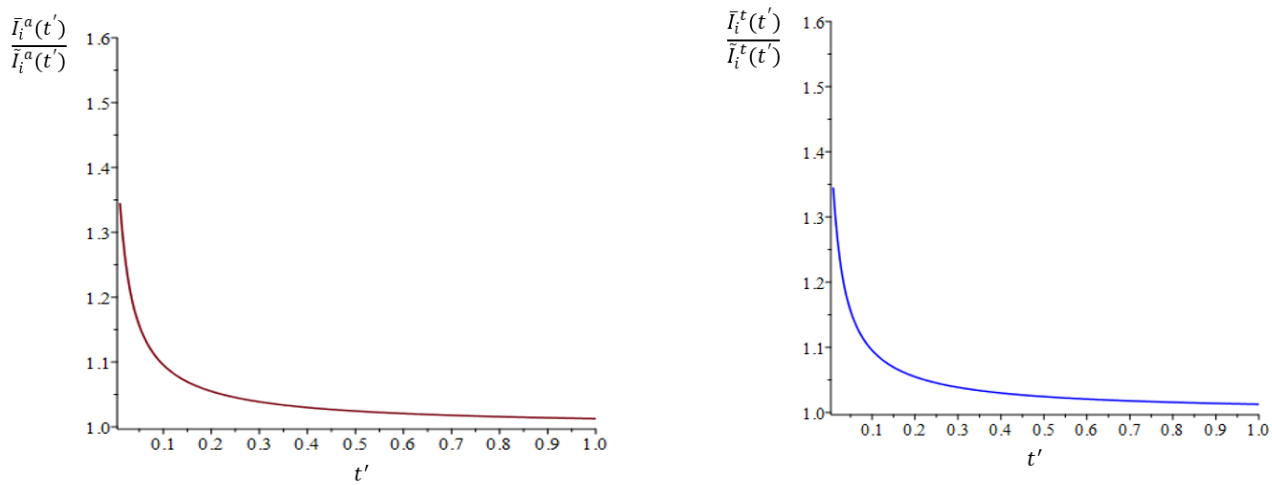
Ports' service differentiation can moderate inter-port competition (Wang et al., 2012), thus affecting port adaptation investment. Ports with more homogenous services should compete more fiercely. For example, Shenzhen and Hong Kong port both focus on container cargo as gateway to the South China, making their competition intense. And ports with more differentiated services compete less intensely. For example, the largest port in Europe, port of Rotterdam (the Netherlands), focuses on container cargo, while the other port in the same region, the port of Antwerp (Belgium), mainly handles bulk cargo. The two ports thus do not compete head-to-head. In this section, we explicitly model such inter-port competition intensity by allowing the shippers in the common hinterland to have a different transport cost parameter compared to each port's captive catchment area. Specifically, we let the shipper in the common hinterland have a different transport cost, t', compared to the transport cost, t, for shippers in two ports' own captive catchment. The parameter t' thus helps capture port service heterogeneity in the common hinterland market. A smaller t' suggests a less port service heterogeneity, equivalent to a more intense inter-port competition. With this new parameter t', the pricing rule at operation stage and optimal adaptation investment at the adaptation investment stage can be solved first. The new equilibrium adaptation with competing port authorities is obtained as $\bar{I}_i^a(t')$ and $\bar{I}_i^t(t')$. The equilibrium adaptation with monopoly port authority is obtained as $\tilde{I}_i^a(t')$ and $\tilde{I}_i^t(t')$ (the expressions of these equilibria are shown in Appendix A4).

The competition effect is measured by ratio $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$. The comparative statics $\frac{\partial}{\partial t'}\left(\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}\right)$ and $\frac{\partial}{\partial t'}\left(\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}\right)$ shed light on the impact of inter-port competition intensity (port service

[21] The Port of San Diego (California) led a multi-stakeholder effort, The Climate Mitigation and Adaptation Plan, with the port terminal operators, nearby communities (Becker et al., 2013).

homogeneity) on the competition effect of port adaptation. However, $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$ are high order polynomial of t', such that the analytical result on comparative statics $\frac{\partial}{\partial t'}\left(\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}\right)$ and $\frac{\partial}{\partial t'}\left(\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}\right)$ is difficult to reach. Numerical simulation is conducted with the parameter values $\Psi = 0.1$, $\eta = 2$, $\omega = 25$, $t = 0.1$. Figure 2.4 shows the numerical values of $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$ with changes in t'. When t' increases, the values of ratios $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$ decrease. That is, when two ports are more competitive, or port services are more homogenous, the competition effect on port adaptation is strengthened. Robustness check has also been done with a wide range of the different parameter values, and our conclusions keep consistent qualitatively. [22]

Figure 2.4 Numerical values of $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$ with changing t' ($\Psi = 0.1$, $\eta = 2$, $\omega = 25$, $t = 0.1$)



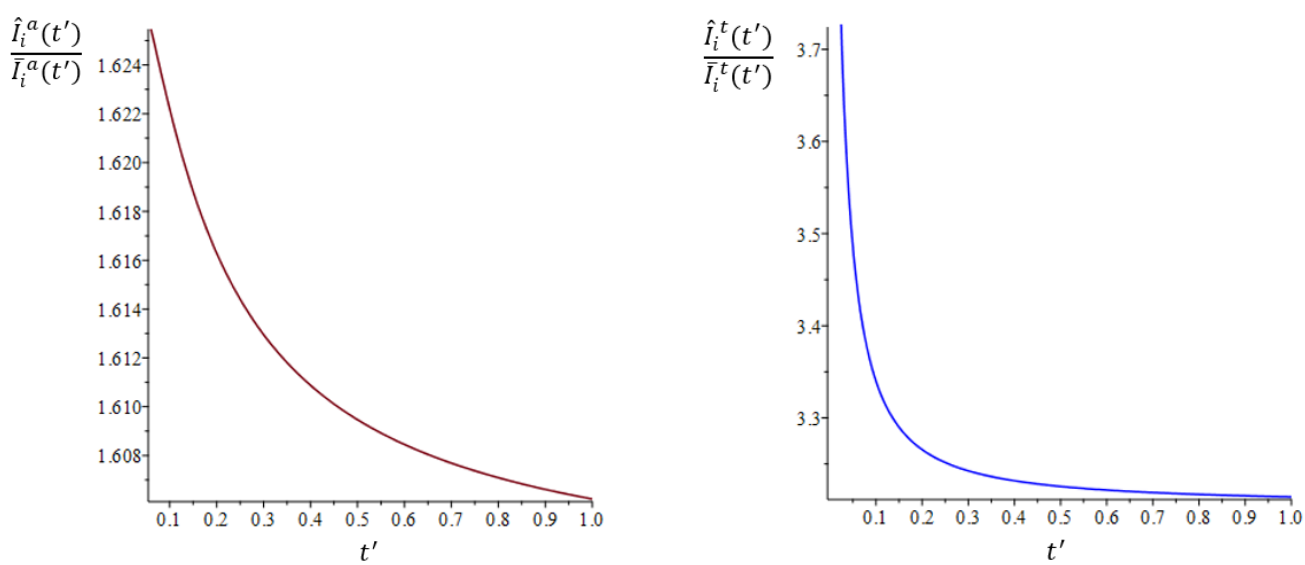
Note: Larger values of $\frac{\bar{I}_i^a(t')}{\tilde{I}_i^a(t')}$ and $\frac{\bar{I}_i^t(t')}{\tilde{I}_i^t(t')}$ suggest a stronger competition effect on port adaptation.

[22] The results of the robustness check with alternative parameter values are available upon request. They are not reported in the manuscript to save space.

In addition, the equilibrium adaptations with competing port authorities but allowing intra-port coordination are solved as $\hat{I}_i^a(t')$ and $\hat{I}_i^t(t')$ with the expressions in Appendix A4.

The free-riding effect is reflected by the ratio $\frac{\hat{I}_i^a(t')}{\bar{I}_i^a(t')}$ and $\frac{\hat{I}_i^t(t')}{\bar{I}_i^t(t')}$. The inter-port competition intensity (port service homogeneity) might also affect incentive of the port authority and terminal operator to free-ride each other on adaptation within one port. Numerical simulation demonstrates the relation between values of $\frac{\hat{I}_i^a(t')}{\bar{I}_i^a(t')}$, $\frac{\hat{I}_i^t(t')}{\bar{I}_i^t(t')}$ and the parameter t' (as Figure 2.5). It is noted when t' increases, the values of ratios $\frac{\hat{I}_i^a(t')}{\bar{I}_i^a(t')}$, $\frac{\hat{I}_i^t(t')}{\bar{I}_i^t(t')}$ decrease as well. This suggests that more intense inter-port competition (more service homogeneity) can strengthen the free-riding effect on adaptation between port authority and terminal operator at the same port. This finding makes sense since when two ports compete more fiercely in the common hinterland market, one port's adaptation contributes more to gain competitive advantage in this competing market. Therefore, within one port, port authority and terminal operator have stronger incentive to free-ride on each other on adaptation. We summarize the effect of inter-port competition intensity (port service homogeneity) on the competition effect and free-riding effect on adaptation as Proposition 2.6.

Figure 2.5 Numerical values of $\frac{\hat{I}_i^a(t')}{\bar{I}_i^a(t')}$ and $\frac{\hat{I}_i^t(t')}{\bar{I}_i^t(t')}$ with changing t' ($\Psi = 0.1$, $\eta = 2$, $\omega = 25$, $t = 0.1$)



Note: Larger values of $\frac{\hat{I}_i^a(t')}{\bar{I}_i^a(t')}$ and $\frac{\hat{I}_i^t(t')}{\bar{I}_i^t(t')}$ suggest a stronger free-riding effect on port adaptation.

Proposition 2.6: *More intense inter-port competition (less service heterogeneity) strengthens both the competition effect on adaptation between two ports, and the free-riding effect on adaptation between port authority and terminal operator within one port.*

2.5 Concluding Remarks

With more than 80% of the global trade carried by international shipping, coastal ports resilience to climate change related disaster is important to maintain reliable global supply chain. Ports around the world are increasingly aware of adaptation to threat of such disasters. This chapter contributes to existing literature in port adaptation on several aspects. First, we model the climate-change related disaster to have a general-form Knightian uncertainty (Knight 1921) in the sense that the probability of the disaster occurrence is per se a random variable and not accurately knowable. Our Knightian uncertainty captures a more general and wider family of probability distributions, not limited to the specific assumptions in Weitzman (2009) and Xiao et al. (2015). The other strand of contributions is to explicitly examine the impacts of inter-port competition, intra-port cooperation on port adaptation investment. We also explicitly model endogenous port pricing and shippers' demand with port adaptation. The study answers how inter-port competition, and intra-port cooperation can increase or decrease the port adaptation.

We find, with Knightian uncertainty assumption, the port adaptation investments increase with the expectation of the disaster occurrence probability but decrease with its variance. In other words, a higher expectation of the disaster occurrence probability encourages port adaptation, but the variance of the disaster occurrence probability discourages port adaptation. Inter-port competition results in more adaptation investment (i.e., the competition effect). There is free-riding between the port authority and the terminal operator (i.e., the free-riding effect) within each port. Their coordination can increase the adaptation by removing such free-riding effect. The expected social welfare of the two-port region increases with ports' adaptation, such that inter-port competition, and intra-port coordination lead to higher expected social welfare. We also find that the competition and free-riding effects on port adaptation can be strengthened by a higher expectation and larger

variance of disaster occurrence probability, and by increasing inter-port competition intensity (less port service homogeneity).

This chapter also opens new avenue for future research. First, the market structure of private terminal operators needs better exploration. We assume each port has a single terminal operator, which can be restrictive. One port can have more than one terminal operator, either private or owned by port authority. Some shipping lines also operate dedicated terminals. In addition, multinational terminal operators such as PSA International, Hutchison Port Holding, APM terminals, DP World and China Merchant Holding can simultaneously operate in several nearby ports. Such intra- and inter-port competition, and inter-port cooperation among private terminal operators can be better accounted for in the future study when analyzing port adaptation. Second, public ownership of port authority and its implication on port adaptation may be also investigated. Although we have explained in the study that most of the port authorities have been corporatized and financially self-responsible, port authority may also partially bear social responsibility. It is reasonable to conjecture that public port authority could invest more on adaptation, especially when port adaptation can have positive externality to protect nearby neighbourhood community and contribute to a more resilient local economy beyond protecting shippers' economic benefits. In addition, public ownership may also reduce port authorities' free-riding effect on terminal operator, as public port authority also accounts for terminal operator's profit in its objective function. Last our study exclusively focuses on the disaster adaptation decision, while port can have multi-dimensional long-term decisions, such as capacity expansion, facilities upgrading etc. With a limited resource, port may need to trade off among adaptation, capacity expansion and other development projects. A more comprehensive economic model is therefore called for to consider port optimal resource allocation for multi-dimension decisions.

Chapter 3. Effects of High-Speed Rail Speed on Airline Demand and Price

3.1 Introduction

With a significantly increased train speed, high-speed rail (HSR) has become an effective competitor of air transport. Studies on intermodal competition show mixed results on the competitive distance of HSR. Adler et al. (2010) find that HSR is most competitive in markets of 750 km or less distance. Chen (2017) finds that the impact of HSR on airlines is the greatest on route distance between 500 km to 800 km. Wan et al. (2016) show that in China, HSR services with a maximum speed of 300 km/hr produce much stronger negative impacts on routes above 800 km than those with a maximum speed of 200 km/h. Therefore, HSR speed plays a critical role in shaping HSR's service substitutability with airlines. In fact, HSR speed is an important service quality that contributes to the vertical differentiation between HSR and air transport (Xia and Zhang, 2016). Furthermore, vertical differentiation in speed may co-exist with passengers' heterogeneous taste in mode preference (i.e., horizontal differentiation). More specifically, given the quality factor (e.g., speed), passengers may not reach consensus on the modal choice. The perceptions and attitudes, habitual behaviors, lifestyle choices, and cultural factors can affect travel mode choice over airlines or HSR (Bennett et al., 1957; Thøgersen, 2006; Blainey et al., 2012). For instance, passengers can have divergent perceptions on airlines and HSR in terms of safety concern, comfort level, and in-vehicle service (Li et al., 2015).

The heterogeneous tastes may lead to different substitutability between airlines and HSR. When route distance increases, passengers spend longer time in traveling. As a result, their personal tastes on service characteristics of different modes can be amplified, they may increasingly regard airline and HSR services as different and less substitutable. On the other hand, airline and HSR services become more substitutable on short-haul routes. For instance, by using survey data from Taiwan's HSR market Li and Schmöcker (2017) find that airline and HSR services are more substitutable on the short-haul routes with HSR travel time between one to two hours.

When the two modes are more substitutable and thus compete more fiercely, HSR speed, as a quality attribute, may have different effects on airlines in terms of price and traffic volume. An increasing number of analytical studies have investigated the intermodal competition between airlines and HSR (Yang and Zhang, 2012; D'Alfonso et al., 2015, 2016; Jiang and Zhang 2016; Talebian and Zou, 2016), but there are no studies, to our best knowledge, that explore how the air-HSR substitutability can moderate the HSR speed impacts on airline traffic and price.

Furthermore, while an increased HSR speed reduces travel time it may, on the other hand, raise safety concern as the existing trains are already at a very high level. This appears the case especially in emerging HSR markets such as China, where the HSR operation experience is still being accumulated and technologies are being fast developed. The speed increase can cause suspicion over the railway safety among travellers, especially after China's "7.23 rear-ending" crash accident in July 2011 (the details of the accident will be discussed in Section 3.3 below). This safety concern may be ongoing, affecting negatively HSR demand.

In this chapter we develop an analytical model to study HSR speed effects on airline traffic and price, explicitly accounting for the potential impact of intermodal substitutability. Our model incorporates, following the above discussion, two countervailing effects of HSR speed on airlines, namely the travel time effect and safety effect, where an increase in HSR speed reduces HSR travel time but may harm public confidence in HSR safety. Apart from investigating whether and how the air-HSR service substitutability can moderate the HSR speed effect, the present chapter is also the first study to analytically incorporate the safety effect of HSR speed.

As a natural and important extension of the analytical model, we empirically test, and quantify, the HSR speed effects on airlines using an event of HSR speed reduction in China. The exercise also allows to verify the theoretical findings. As will be elaborated in Section 3.3, this HSR speed reduction in China in 2011 largely alleviates the endogeneity concern over HSR speed effect estimation. Briefly, this is because the reduction was enforced by the government rather than being a market competition outcome, and it was implemented system-wide (independent of any route heterogeneity). A difference-in-differences (DID) method is employed to estimate equations of

airline traffic and price.[23] In line with theoretical analysis, we identify varying HSR speed effects when airline and HSR services are differently substitutable.

The theoretical model shows that the air-HSR substitutability reinforces the HSR speed effect on airlines, and that the speed effect depends further on the relative dominance of the travel-time and safety effects. A HSR speed reduction increases airline traffic and price when the travel-time effect dominates, while it reduces airline traffic and price when the safety effect dominates. Moreover, HSR speed has a larger impact on airline traffic than on airline price. Finally, our analysis suggests that the speed effect can be moderated by the intensity of inter-airlines competition.

The empirical results are largely consistent with the theoretical findings. Specifically, the HSR speed reduction increased both airline traffic and price, implying that in the Chinese market we examined, the travel-time effect dominates the safety effect of a HSR speed change. More importantly, the estimation shows that the HSR speed effect on airlines is much stronger on short-haul routes than on long-haul routes, where airlines and HSR are less substitutable. This result is robust with alternative econometric specifications. By conducting model selection tests, we find that the HSR speed effect on airlines declines with route distance but increases with HSR speed in a square relation. The HSR speed effect is thus very responsive to air-HSR substitutability.

The remainder of this chapter is organized as follows. Literature review is provided in Section 3.2. Section 3.3 briefly discusses HSR development in China and the system-wide HSR speed reduction in 2011, which is used as a natural experiment to estimate HSR speed effects. Section 3.4 develops a theoretical model, and Section 3.5 specifies the econometric model and discusses data sources and variables. Estimation results are presented in Section 3.6. The last section, Section 3.7, summarizes this chapter.

3.2 Literature Review

This literature review consists of two parts. The first part reviews major studies on air-HSR competition, focusing on the travel time and safety issues. The second part discusses the literature

[23] See Ashenfelter and Card (1985) for the details on the DID estimation method and application.

on the interactions of horizontal and vertical differentiation, with an emphasis on the research gaps in the context of air-HSR competition.

3.2.1 Air-HSR competition

One stream of the literature analytically investigates the effects of air-HSR competition. Yang and Zhang (2012), using an adapted Hotelling model, find that both airfare and rail fare fall as HSR put more weight on social welfare in the objective function. D'Alfonso et al. (2015) analyze the environmental impact of air-HSR competition and show that the introduction of HSR may have a negative effect on the environment. Jiang and Zhang (2016) investigate the long-term impacts of HSR competition on airlines and find that the airline, faced with stronger competition from HSR, will more likely move towards a hub-and-spoke network. Talebian and Zou (2016) find that the HSR operator focusing more on social welfare will benefit passengers through reduced fare and higher frequency. However, some gaps exist among the current analytical studies on air-HSR competition. First, Yang and Zhang (2012), D'Alfonso et al. (2015) and Talebian and Zou (2016) have modeled HSR speed as a decision variable. D'Alfonso et al. (2015) focus on the environmental effect of HSR speed while the other two focus on the travel time effect of HSR speed. However, the safety effect of HSR speed has not yet been explicitly considered. Second, existing analytical studies on air-HSR interactions largely deal with a duopoly market (i.e., one HSR and one airline), for example, Yang and Zhang (2012), D'Alfonso et al. (2015, 2016), Jiang and Zhang (2016), and Talebian and Zou (2016). However, inter-airlines competition within the air sector in the presence of HSR has rarely been modeled.

Another stream of literature empirically investigates air-HSR competition, focusing on the travel-time effect. For instance, González-Savignat (2004) analyzes the potential for HSR to compete with airlines in the Madrid-Barcelona market, and finds that the impact on airlines depends on HSR travel time. Dobruszkes (2011) considers HSR travel time as a key competitive factor. Behrens and Pels (2012) study the travelers' behavior in the London-Paris market and find that HSR market share is influenced by total travel time. Capozza (2016) tests how HSR travel time affects airfare using the market data of Italy and finds that airlines set, on average, higher fares as rail travel time increases. Zhang et al. (2017) find that airline demand falls as HSR travel time becomes shorter in

the Chinese market. However, the endogeneity issue has not been well addressed in the above-mentioned studies. For instance, cross-sectional data is used in Capozza (2016), so the route-level unobservables cannot be controlled. Zhang et al. (2017) adopt panel data, but the fixed-effect model cannot be used to control the route-level unobservables, because HSR travel time is time-invariant during the sample period.

In addition, the safety concern due to HSR speed change may not be trivial, as empirical literature demonstrates that travellers demand higher safety when choosing transport modes. Janic (2003) evaluates HSR, Maglev and air transport in Europe using multiple criteria and finds that safety is related to the perceived risk of injury and/or death due to an accident, and is of particular interest for the users of high-speed systems. Chou and Kim (2009) analyze the actual riding experience on the Taiwan HSR (THSR) and Korea Train eXpress (KTX) and find that rider security is one of the key factors of service quality that affects customer satisfaction. Chou et al. (2011) evaluate HSR service quality and performance by interviewing THSR and KTX passengers, and find that the top importance measurement indicator for TSHR passengers is the safety of the HSR. Kuo and Tang (2013) show that satisfaction directly affects travel behaviors, and maintain transportation safety are essential considerations, especially in an aging society. Chou et al. (2014) find that safety is one of the service quality dimensions that affect customer satisfaction and loyalty for THSR services. Wang et al. (2017b) survey more than 300 Chinese inter-urban travellers and find that the perception on the mode safety is one of the most important factors in determining their modal choice among coach, conventional train, HSR and airlines. In addition, Banister (2011) points out that the growth in travel distance needs to be reassessed with a view to reduce it, as shorter distances and slower travel have positive co-benefits for the environment (including safety), energy (and carbon), social inclusion, wellbeing (including health) and the economy. Givoni and Banister (2012) also argue that more important than average speed is the journey reliability, comfort, security and safety and service frequency, all of which make up the journey experience, while achieving high quality for these components that include a rail segment might often mean compromising on the maximum speed.

However, the safety effect due to HSR speed change is omitted in the existing literature of air-HSR competition. More importantly, very few studies have directly and systematically verified the HSR speed effect on airlines, as well as the magnitude, if such impacts do exist. One possible reason is

that there is little variation in HSR speed in countries that operate HSR over the years. As will be discussed in Section 3.3, the system-wide HSR speed reduction in China in 2011 provides a rare natural experiment to unbiasedly estimate the HSR speed effect on airlines.

3.2.2 Interactions of horizontal differentiation and vertical differentiation

The interactions of product substitutability (horizontal differentiation) and service quality (vertical differentiation) have been well studied in industrial organization literature. For instance, Neven and Thisse (1990) analyze a duopoly model with both horizontal (variety) and vertical (quality) differentiation and find that firms choose maximum differentiation along one of the characteristics and minimum differentiation along the other. Degryse (1996) shows that more closely located (more substitutable) banks compete more fiercely on the service quality. Ferreira and Thisse (1996) adopt a revised Hotelling model to investigate the product vertical-horizontal differentiation interaction. The product substitutability is shown to enhance the impact of vertical differentiation on firms' equilibrium price and profit.

In the context of the airline-HSR competition, HSR speed, as a service quality, presumably has a stronger effect on airlines when the two modes are more substitutable (e.g., on shorter haul routes), while the effect may diminish when the services are less substitutable (e.g., on longer haul routes). We are not aware of any studies on air-HSR competition that analytically investigate and empirically test the interactions of horizontal differentiation (air-HSR substitutability based on distance) and vertical differentiation (service quality based on speed).

3.3 A Natural Experiment in HSR Speed Reduction

To modernize the country's railway transport system and to alleviate rail capacity constraint, China announced a "Mid-to-Long-Term Railway Network Plan" in 2004 and laid out a blueprint of

building a "4+4" HSR network with a total length of 16,000 km by 2020.[24] By the end of 2017, China has already built 25,000 km HSR, longer than the combination of all the other countries. The dramatic HSR construction in the first several years raised significant safety concern. In April 2011, Ministry of Railway planned to slow down HSR operating speed due to reasons that China only had 3 years of experience in HSR operation, and the HSR network was expanding too fast to be totally free of technical flaws. On July 1st 2011, the maximum operating speed on Wuhan-Guangzhou, Zhengzhou-Xi'an, Shanghai-Nanjing HSR lines slowed from 350 km/hr to 300 km/hr. On July 23, a serious crash happened due to signal failures on the Yong-Wen HSR track, where one train collided with another stopped train, killed 40 passengers. The 7.23 rear-ending accident showed some weaknesses in HSR planning and monitoring, which triggered the decision to slow HSR speed system-wide, affecting 498 pairs of trains belonging to 18 railway sub-bureaus, with the maximum operating speed for trains of 350 km/hr reduced to 300 km/hr, 250 km/hr reduced to 200 km/hr, and 200 km/hr reduced to 160 km/hr. For instance, the Beijing-Tianjin, Shanghai-Hangzhou HSR reduced speed from 350 km/hr to 300 km/hr soon after the accident. The Beijing-Shanghai HSR inaugurated on July 1, 2011 and runs at a speed of 300 km/hr, despite the designed maximum speed of 380 km/hr. The decision was designed to accumulate safety management experience, which increases passengers' travel time, but "half an hour is a good price to pay for safety" as stated by the Ministry of Railways.[25]

This major overall drop in HSR speed represents the first time that China's railway authorities have gone against the long-standing policy of acceleration (with a total of six times of rail speed increase since 1997). This speed reduction in China has provided a rare natural experiment to study effects of HSR speed on competing airlines' market demand and price.[26] As already explained, such speed reduction is exogenous as it is of safety concern instead of a market competition outcome. The

[24] The four vertical HSR corridors are Beijing-Shanghai, Beijing-Guangzhou-Shenzhen, Beijing-Harbin, and Hangzhou-Fuzhou-Shenzhen, whereas the four horizontal HSR corridors are Qingdao-Taiyuan, Xuzhou-Lanzhou, Shanghai-Wuhan-Chengdu, and Shanghai-Kunming.

[25] The HSR operator did not shorten the stopping time at each railway station to make up for the travel time loss due to the speed reduction.

[26] Bilotkach et al. (2012) investigate the sensitivity of prices to demand shocks in a natural experiment that occurred in the San Francisco Bay Area where a freeway interchange collapse after an accident, making OAK airport a less attractive choice than SFO airport. The study reveals that the surface road infrastructure disruption reduced airfare by 6-7% at the affected airports.

speed reduction was mandated by the government and implemented on all HSR routes almost at the same time, which makes it independent of route heterogeneous characteristics. Potential endogeneity of HSR speed is minimized to the largest extent for empirical estimation. This speed reduction effect has been ongoing since its implementation in 2011. The maximum operating speed on Beijing-Shanghai line, however, resumed to 350km/hr in September 2017, after accumulating HSR operation experience and going through rigorous evaluation on current HSR safety standard.

HSR price in China is strictly regulated. Although China's Railway Corporation announced in March 2017 that the price of some HSR lines will be adjusted based on market condition, the exact timeline has not yet been settled.[27] The HSR baseline price is 0.45 RMB per km (about 0.07 USD), applied to every route.[28] Even when the speed was reduced in 2011, HSR price remained almost the same,[29] while HSR in Europe has much autonomy to set price, taking into account the heterogeneous market conditions.

The 7.23 rear-ending accident could also result in confidence loss and panic in traveling by HSR. This panic can also divert travel demand from HSR to airlines in the short term, which might create a confounding factor on the speed reduction effect. For example, Wei et al. (2017) find that, on the newly opened Beijing-Shanghai HSR line, airline price increased by 27.4% within the first half month immediately post the accident. Thus, our empirical estimation must disentangle the speed reduction (HSR service quality) effect from the potential short-term panic effect.[30] Unlike the speed effect that can be persistent over time, this panic effect could attenuate fast. This nature helps us identify them separately.

---

[27] See the article from China Daily at http://www.chinadaily.com.cn/opinion/2017-03/27/content_28686754.htm.

[28] See the article from Xinhua News Agency of China at http://news.xinhuanet.com/politics/2016-02/28/c_128758428.htm.

[29] The ticket price of some HSR lines was reduced by at most 5% after the speed reduction: http://news.xinhuanet.com/politics/2016-02/28/c_128758428.htm.

[30] This is similar to Ito and Lee (2005) who find that the impact of "9-11" on the US air travel demand consists of: i) a negative "transitory" shock (over 30%); and ii) an "ongoing" negative demand shock. The latter is due to the increased security measures. In particular, the stringent new security requirements that were implemented as a direct result of the September 11th terrorist attacks have made pre-departure procedures more cumbersome and time-consuming, an effect often referred to as the "hassle factor." Ito and Lee (2005) are able to empirically detect this hassle factor.

3.4 Analytical Model

3.4.1 Demand side

Suppose that a representative passenger maximizes the following net utility from travelling by airlines and HSR: [31]

$$\underset{\{q_A, q_H\}}{\text{Max}}\ U\ (q_A,\ q_H) - \bar{P}_A q_A - \bar{P}_H q_H \tag{3.1}$$

where $U(q_A, q_H)$ is the gross utility of travel in the sense that it excludes the generalized travel costs, which consist of out-of-pocket money, time-related and safety-related costs involved in travel. $\bar{P}_i$ and q_i represent the generalized travel costs and the quantity of travel mode i, with $i = A$ or H standing for airlines or HSR, respectively. The generalized travel costs perceived by travelers are:

$$\bar{P}_A = P_A \tag{3.2.1}$$

$$\bar{P}_H = P_H + \mathcal{T}(s_H(\bar{s}_H)) + \mathcal{S}(\bar{s}_H) \tag{3.2.2}$$

where P_i is the ticket price of transport mode i, $\bar{s}_H$ is the maximum HSR operating speed, and s_H is the average HSR operating speed. $\mathcal{T}$ and $\mathcal{S}$ capture, respectively, the travel-time effect and safety effect of HSR speed, measured in monetary term. The travel time that passengers experience is a factor of the average HSR speed, which depends on the maximum HSR speed, the number of stops on the HSR line, the percentage of the line on which the maximum speed can be achieved, as well as weather conditions (Givoni and Banister, 2012).[32] In this analysis, we assume that average speed s_H is a monotonically increasing function of maximum speed $\bar{s}_H$ and treat the other factors as given. This could be a reasonable assumption, because in general higher average speed is usually

[31] We assume the representative passenger to represent the average travel utility of possibly different types of passengers in response to the travel modes' characteristics.

[32] Since the function $\mathcal{T}(s_H(\bar{s}_H))$ is quite general, it can capture the access/egress travel time effect (which is treated as constant), besides the in-vehicle travel time in our analysis.

achieved on HSR lines with higher maximum operating speed. On the other hand, passengers may perceive HSR with a higher maximum speed as less safe, because faster speed is usually associated with higher risk of an accident and casualties.[33] The function $\mathcal{S}(\bar{s}_H)$ may not be linear in the sense that when speed is low, an increase of HSR speed limit may not raise much safety concern, while when speed is fast (e.g., 300 km/hr or above), an increase of maximum HSR speed may raise sufficient safety concern. Therefore, a HSR with faster speed limit enhances the total travel time advantage of HSR relative to air transport but may cause disutility due to the perceived safety concern. Hence, $\partial\mathcal{T}/\partial\bar{s}_H < 0$ [34] and $\partial\mathcal{S}/\partial\bar{s}_H > 0$.

We obtain the inverse demand function of travel mode i by solving Eq. (3.1):

$$P_A = \rho_A(q_A, q_H) \tag{3.3.1}$$

$$P_H = \rho_H(q_A, q_H) - \mathcal{T}(s_H(\bar{s}_H)) - \mathcal{S}(\bar{s}_H) \tag{3.3.2}$$

where $\rho_i(q_A, q_H) = \frac{\partial U(q_A, q_H)}{\partial q_i}$, which stands for the marginal utility with respect to q_i.

Differentiating Eq. (3.3.1) and Eq. (3.3.2) with respect to $\bar{s}_H$ and solving for the partial derivatives of demand with respect to $\bar{s}_H$ yield Eq. (3.4.1) and Eq. (3.4.2) [35]:

$$\frac{\partial q_A}{\partial \bar{s}_H} = -\frac{\left(\overbrace{\frac{\partial \mathcal{T}}{\partial \bar{s}_H}}^{<0} + \overbrace{\frac{\partial \mathcal{S}}{\partial \bar{s}_H}}^{>0}\right)\overbrace{\frac{\partial \rho_A}{\partial q_H}}^{<0}}{\underbrace{\frac{\partial \rho_H}{\partial q_H}\frac{\partial \rho_A}{\partial q_A} - \frac{\partial \rho_H}{\partial q_A}\frac{\partial \rho_A}{\partial q_H}}_{>0}} \tag{3.4.1}$$

[33] We assume safety effect is a function of maximum HSR speed instead of average HSR speed, because passengers may not have full information of the average operating speed, but are fully aware of the maximum speed.

[34] $\frac{\partial \mathcal{T}}{\partial \bar{s}_H} = \underbrace{\frac{\partial \mathcal{T}}{\partial s_H}}_{<0}\underbrace{\frac{\partial s_H}{\partial \bar{s}_H}}_{>0} < 0.$

[35] The HSR speed effect in our analysis refers to the effect of HSR maximum speed, corresponding to the natural experiment in China, where the speed limit was adjusted. However, for the sake of brevity, we use the phrase "HSR speed effect" instead of "HSR maximum speed effect" in the following analysis.

$$\frac{\partial q_H}{\partial \bar{s}_H} = \frac{(\overbrace{\frac{\partial \mathcal{T}}{\partial \bar{s}_H}}^{<0} + \overbrace{\frac{\partial \mathcal{S}}{\partial \bar{s}_H}}^{>0}) \overbrace{\frac{\partial \rho_A}{\partial q_A}}^{<0}}{\underbrace{\frac{\partial \rho_H}{\partial q_H}\frac{\partial \rho_A}{\partial q_A} - \frac{\partial \rho_H}{\partial q_A}\frac{\partial \rho_A}{\partial q_H}}_{>0}} \tag{3.4.2}$$

Assuming U to be strictly concave in (q_A, q_H), we have two properties: (i). definiteness $\frac{\partial \rho_H}{\partial q_H}\frac{\partial \rho_A}{\partial q_A} - \frac{\partial \rho_H}{\partial q_A}\frac{\partial \rho_A}{\partial q_H} > 0$; and (ii). slutsky symmetry $\frac{\partial \rho_H}{\partial q_A} = \frac{\partial \rho_A}{\partial q_H}$ (Dixit, 1986). Given the diminishing marginal utility of travel, suggested by a downward sloping demand curve, we have $\frac{\partial \rho_A}{\partial q_H} < 0$ and $\frac{\partial \rho_A}{\partial q_A} < 0$. Therefore, when travel-time effect dominates safety effect ($\partial \mathcal{T}/\partial \bar{s}_H + \partial \mathcal{S}/\partial \bar{s}_H < 0$), we have $\frac{\partial q_A}{\partial s_H} < 0$ and $\frac{\partial q_H}{\partial s_H} > 0$, while when safety effect dominates ($\partial \mathcal{T}/\partial \bar{s}_H + \partial \mathcal{S}/\partial \bar{s}_H > 0$), $\frac{\partial q_A}{\partial s_H} > 0$ and $\frac{\partial q_H}{\partial s_H} < 0$. Thus, an increasing HSR speed can increase or decrease HSR/airline demand, depending on which effect (travel-time vs. safety) dominates. By assuming symmetry ($\frac{\partial \rho_H}{\partial q_H} = \frac{\partial \rho_A}{\partial q_A}$) and from the two properties (definiteness and Slutsky symmetry), we have $\left|\frac{\partial \rho_A}{\partial q_A}\right| > \left|\frac{\partial \rho_A}{\partial q_H}\right|$. Comparing Eq. (3.4.1) and Eq. (3.4.2), we obtain $\left|\frac{\partial q_H}{\partial \bar{s}_H}\right| > \left|\frac{\partial q_A}{\partial \bar{s}_H}\right|$. Thus, HSR speed has a larger impact on HSR demand than on airline demand.

As discussed in Section 3.3 since HSR price is fixed in China[36], we can derive the partial derivative of airline price to $\bar{s}_H$ in Eq. (3.5) by taking P_H as given. The effect of HSR speed on airline price again depends on the sign of $\partial \mathcal{T}/\partial \bar{s}_H + \partial \mathcal{S}/\partial \bar{s}_H$ as:

$$\frac{\partial P_A}{\partial \bar{s}_H} = \frac{\overbrace{\frac{\partial \rho_A}{\partial q_H}}^{<0}}{\underbrace{\frac{\partial \rho_H}{\partial q_H}}_{<0}} (\overbrace{\frac{\partial \mathcal{T}}{\partial \bar{s}_H}}^{<0} + \overbrace{\frac{\partial \mathcal{S}}{\partial \bar{s}_H}}^{>0}) \tag{3.5}$$

[36] Assuming fixed HSR price is not a strong assumption. Besides China, HSR price in several regions is largely fixed and does not vary as much as airfares. For example, in Japan, the price on Tokaido line is fixed, despite of only a JPY200 discount during off-peak season. In Taiwan, HSR operator offers only a limited quantity of early bird discount, but when the early bird tickets are sold out, regular and fixed fares apply. In South Korea, the HSR prices from Seoul to Daegu, Daejeon and Busan are fixed.

It should be noted that the demand and price here are not the equilibrium resulting from market competition outcome. After taking into account the supply side in the next subsection, we will show that the same result holds for the equilibrium traffic and price.

3.4.2 Supply side

Airlines are assumed to be symmetric in cost structure and provide homogenous air service. We assume that N airlines engage in Cournot competition.[37] However, since HSR price is assumed to be fixed regardless of speed change, it is impossible to explicitly model the competition between airlines and HSR, as well as the cost structure of HSR through speed variation.[38] The HSR speed effect on airlines is thus only through the demand side. This analysis thus should be better interpreted as partial equilibrium, without fully accounting for possible strategic behavior of the HSR operator. We write the inverse airline demand function as $P_A(q_A, \bar{s}_H)$. A single airline maximizes the profit with respect to its own quantity q_j^A. [39]

$$\underset{q_j^A}{\text{Max}}\ \pi_j^A = (P_A(q_A, \bar{s}_H) - c)\, q_j^A \tag{3.6}$$

where $q_A = \sum_{j=1}^{N} q_j^A$ is the total air traffic, and c is the airline's common constant marginal cost. The first-order condition (FOC) of Eq. (3.6) with respect to q_j^A gives:

---

[37] Empirical evidence suggests that rivalry between oligopoly airlines may be consistent with Cournot behavior (e.g., Brander and Zhang, 1990, 1993; Oum et al., 1993; Lijesen and Behrens, 2017). In addition, Cournot behavior among airlines has been assumed in theoretical studies in airline alliance (e.g., Park, 1997; Brueckner, 2001; Zhang and Zhang, 2006a; Bilotkach, 2007; Brueckner and Proost, 2010), airport congestion pricing (e.g., Zhang and Zhang, 2006b; Basso and Zhang, 2007; Basso, 2008; Zhang and Zhang, 2010) and airline-HSR cooperation (Xia and Zhang, 2016).

[38] Empirical evidence also confirms the positive relation between HSR speed and operating cost, since maintaining higher speed requires more energy consumption (Kemp, 2004; Andersson and Lukaszewicz, 2006; Álvarez, 2010; Bosquet et al., 2013; D'Alfonso et al., 2016). However, we abstract away the potential mechanism that the HSR operating cost changes due to speed variation, which could be reflected on HSR price through its strategic interaction with airlines.

[39] We also examined more general cases other than Cournot competition. We define $\frac{\partial q_{-j}^A}{\partial q_j^A} = (N-1)\frac{\partial q_h^A}{\partial q_j^A}$, with the conjectural variation $\delta = \frac{\partial q_h^A}{\partial q_j^A} \in [0,1]$ ($h \neq j$), as in Brander and Zhang (1990; 1993) and Oum et al. (1995). The values of 0 and 1 for δ represent the Cournot and cartel airline competition, respectively. The larger the δ, the more collusion or less competition among the airlines. The result with a positive δ gives similar results, indicating that our analysis is not constrained to Cournot competition among airlines. The detailed derivations and results are available upon request from the authors.

$$(P_A - c) + q_j^A \frac{\partial P_A}{\partial q_A} = 0 \tag{3.7}$$

By imposing symmetry and totally differentiating FOC with respect to $\bar{s}_H$, we can obtain how the equilibrium airline traffic q_A^* changes with $\bar{s}_H$:

$$\frac{dq_A^*}{d\bar{s}_H} = \underbrace{-\frac{\frac{\partial P_A}{\partial \bar{s}_H} + \frac{q_A}{N}\frac{\partial^2 P_A}{\partial q_A \partial \bar{s}_H}}{(1+\frac{1}{N})\frac{\partial P_A}{\partial q_A} + \frac{q_A}{N}\frac{\partial^2 P_A}{\partial q_A^2}}}_{<0} \tag{3.8}$$

In case of linear demand, $\frac{\partial^2 P_A}{\partial q_A \partial \bar{s}_H} = 0$. In case of non-linear demand, if $\frac{\partial^2 P_A}{\partial q_A \partial \bar{s}_H}$ is small in magnitude, the sign of $\frac{dq_A^*}{d\bar{s}_H}$ follows the sign of $\frac{\partial P_A}{\partial \bar{s}_H}$ (Eq. (3.5)). As a result, $\frac{\partial q_A^*}{\partial s_H} < (>) 0$ if $\partial \mathcal{T}/\partial \bar{s}_H + \partial \mathcal{S}/\partial \bar{s}_H < (>) 0$. Therefore, the equilibrium airline demand decreases (increases) with HSR speed when travel-time (safety) effect is dominant.

Next, we write the airline demand function as $q_A(P_A, \bar{s}_H)$. Rearranging the FOC and totally differentiating it with respect to $\bar{s}_H$, we obtain how the equilibrium airline price P_A^* changes with $\bar{s}_H$:

$$\frac{dP_A^*}{d\bar{s}_H} = \underbrace{-\frac{\frac{1}{N}\frac{\partial q_A}{\partial \bar{s}_H} + (P_A - c)\frac{\partial^2 q_A}{\partial P_A \partial \bar{s}_H}}{\left(1+\frac{1}{N}\right)\frac{\partial q_A}{\partial P_A} + (P_A - c)\frac{\partial^2 q_A}{\partial {P_A}^2}}}_{<0} \tag{3.9}$$

Similar as the discussion for Eq. (3.8), in case of linear demand, $\frac{\partial^2 q_A}{\partial P_A \partial \bar{s}_H} = 0$; or in case of non-linear demand, if $\frac{\partial^2 q_A}{\partial P_A \partial \bar{s}_H}$ is small in magnitude, the sign of $\frac{\partial P_A^*}{\partial \bar{s}_H}$ follows the sign of $\frac{\partial q_A}{\partial \bar{s}_H}$ (Eq. (3.4.1)). As a result, $\frac{\partial P_A^*}{\partial \bar{s}_H} < (>) 0$ if $\partial \mathcal{T}/\partial \bar{s}_H + \partial \mathcal{S}/\partial \bar{s}_H < (>) 0$. Therefore, the equilibrium airline price decreases (increases) with HSR speed when travel-time (safety) effect is dominant. We summarize the above discussion in Proposition 3.1, and the detailed proof is relegated to Appendix B1.

Proposition 3.1: *When HSR travel-time effect dominates the safety effect, i.e.,* $\partial\mathcal{T}/\partial\bar{s}_H + \partial\mathcal{S}/\partial\bar{s}_H < 0$*, airline traffic and price decrease with HSR speed; while when the safety effect dominates travel-time effect, i.e.,* $\partial\mathcal{T}/\partial\bar{s}_H + \partial\mathcal{S}/\partial\bar{s}_H > 0$*, airline traffic and price increase with HSR speed.*

Although Proposition 3.1 is intuitive, the analysis incorporates the trade-off between the travel-time and safety effects, contrary to the existing analytical literature that only examines the HSR travel-time effect on airlines (e.g., Yang and Zhang, 2012; D'Alfonso et al., 2015; Talebian and Zou, 2016; Xia and Zhang, 2016, 2017). As discussed earlier, this consideration is especially important in emerging HSR markets, such as China, where HSR technology is just being introduced and fast developed before maturity.

In order to investigate how the air-HSR substitutability can alter the HSR speed effect on airline traffic and price, we introduce a quadratic utility function as in Singh and Vives (1984) and Vives (1999, Chapter 6) [40]:

$$U(q_A, q_H) = \alpha_A q_A + \alpha_H q_H - (\frac{1}{2}\beta_A (q_A)^2 + \frac{1}{2}\beta_A (q_H)^2 + \gamma q_A q_H) \tag{3.10}$$

This approach has been widely used in transport literature (e.g., Fu et al., 2006; Flores-Fillol and Moner-Colonques, 2007; Oum and Fu, 2007; Clark et al., 2009, 2011; Socorro and Betancor, 2010; Socorro and Viecens, 2013; Jiang and Zhang, 2014; D'Alfonso et al., 2015, 2016; Talebian and Zou, 2016). However, our model has several distinctions. First, we consider an industry with two sectors (air sector and rail sector) producing differentiated goods, and the air sector consists of multiple firms producing homogeneous goods, while the above studies mainly consider a duopolistic industry with two firms. Second, we introduce both horizontal and vertical differentiation in the sense that consumers have heterogeneous preference over air and rail services ceteris paribus, but they uniformly prefer the safer and faster transport mode given the same price. We thus analyze the interactions between vertical and horizontal differentiation in the context of

[40] Singh and Vives (1984) focus on the duality of price and quantity competition in a differentiated duopoly, and analyze the dominant strategy for each firm given the substitutability (complementarity) of products. Vives (1999, Chapter 6) considers both quantity and price competition, and focuses on the existence and uniqueness of quantity and price equilibria, as well as characterizes and compares those equilibria.

air-HSR competition, which has not been examined before. Third, the safety effect of HSR speed has yet been explicitly modeled in the existing analytical studies.

α_A and α_H in Eq. (3.10) measure the potential market size for airlines and HSR, respectively. $\gamma \in [0,1]$ measures the air-HSR substitutability. A small value of γ implies that airline and HSR are less substitutable, while a large value of γ suggests that HSR and airlines services are more homogenous and substitutable. As discussed earlier, we expect that airlines and HSR are more substitutable on short-haul routes. Substitutability γ captures horizontal differentiation, while $\mathcal{T}(s_H(\bar{s}_H))$ and $\mathcal{S}(\bar{s}_H)$ indicate vertical differentiation (i.e., quality offered by HSR due to speed variation). Our model thus introduces the interaction of both service substitutability and quality. For simplicity, we assume $\beta_A = \beta_H = 1$ (i.e., price sensitivities of demands is 1). However, this assumption is without loss of generality, because all the results hold when $\beta_A\beta_H - \gamma^2 > 0$, which is true due to the definitiveness of the quadratic utility function (Dixit 1986). The travel demand with the quadratic utility is derived as follows:

$$q_A = \frac{\alpha_A - P_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S}))}{1 - \gamma^2} \tag{3.11.1}$$

$$q_H = \frac{\alpha_H - P_H - (\mathcal{T} + \mathcal{S}) - \gamma(\alpha_A - P_A)}{1 - \gamma^2} \tag{3.11.2}$$

Before taking into account the supply side of airline competition, the elasticity of airline demand q_A with respect to $\bar{s}_H$ (conditional on the price which may not be the equilibrium) is derived in Eq. (3.12). Thus, the sign of $\varepsilon_{q_A,\bar{s}_H}$ still depends on the relative dominance of the travel-time and safety effect of HSR speed change, i.e., $\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H}$.

$$\varepsilon_{q_A,\bar{s}_H} = \frac{\partial q_A}{\partial \bar{s}_H}\frac{\bar{s}_H}{q_A} = \frac{\gamma\, \bar{s}_H(\overbrace{\frac{\partial \mathcal{T}}{\partial \bar{s}_H}}^{<0} + \overbrace{\frac{\partial \mathcal{S}}{\partial \bar{s}_H}}^{>0})}{\underbrace{\alpha_A - P_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S}))}_{>0}} \tag{3.12}$$

With the quadratic utility function, the equilibrium individual airline traffic $q_{i,A}^*$, the equilibrium total airline traffic q_A^*, and the equilibrium airline price P_A^* are derived as follows:

$$q_{i,A}^* = \frac{\alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S})) - c}{(1-\gamma^2)(1+N)} \tag{3.13.1}$$

$$q_A^* = N\frac{\alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S})) - c}{(1-\gamma^2)(1+N)} \tag{3.13.2}$$

$$P_A^* = \frac{Nc + \alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S}))}{1+N} \tag{3.13.3}$$

We next investigate how equilibrium airline traffic $q_{i,A}^*$ and price P_A^* change with HSR speed $\bar{s}_H$.

$$\frac{dq_{i,A}^*}{d\bar{s}_H} = \frac{\gamma(\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H})}{(1-\gamma^2)(1+N)} \tag{3.14.1}$$

$$\frac{dq_A^*}{d\bar{s}_H} = \frac{N\gamma(\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H})}{(1-\gamma^2)(1+N)} \tag{3.14.2}$$

$$\frac{dP_A^*}{d\bar{s}_H} = \frac{\gamma(\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H})}{1+N} \tag{3.14.3}$$

Consistent with the discussion of Eq. (3.8) and (3.9), the signs of Eq. (3.14.1) - (3.14.3) depend on the relative dominance of travel-time and safety effect, i.e., $\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H}$. We can obtain the elasticity of equilibrium airline traffic with respect to $\bar{s}_H$ and the elasticity of equilibrium airline price with respect to $\bar{s}_H$ in Eq. (3.15.1) and Eq. (3.15.2), respectively:

$$\varepsilon_{q_A^*,\bar{s}_H} = \varepsilon_{q_{i,A}^*,\bar{s}_H} = \frac{dq_A^*}{d\bar{s}_H}\frac{\bar{s}_H}{q_A^*} = \frac{\bar{s}_H\gamma(\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H})}{\underbrace{\alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S})) - c}_{>0}} \tag{3.15.1}$$

$$\varepsilon_{P_A^*,\bar{s}_H} = \frac{dP_A^*}{d\bar{s}_H}\frac{\bar{s}_H}{P_A^*} = \frac{\bar{s}_H\gamma(\frac{\partial \mathcal{T}}{\partial \bar{s}_H} + \frac{\partial \mathcal{S}}{\partial \bar{s}_H})}{\underbrace{Nc + \alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T} + \mathcal{S}))}_{>0}} \tag{3.15.2}$$

Comparing the magnitudes of elasticities with respect to HSR speed, we obtain Eq. (3.16), which indicates that HSR speed change has a larger effect on airline traffic than on airline price. We thus have Proposition 3.2.

$$\left|\varepsilon_{q_A^*,\bar{s}_H}\right| - \left|\varepsilon_{P_A^*,\bar{s}_H}\right| = \frac{c\bar{s}_H\gamma(1+N)\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H}+\frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|}{(\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))-c)\big(Nc+\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))\big)} > 0 \tag{3.16}$$

Proposition 3.2: *With quadratic utility function, the magnitude of elasticity of airline traffic with respect to HSR speed is larger than that of airline price, i.e.,* $\left|\varepsilon_{q_A^*,\bar{s}_H}\right| > \left|\varepsilon_{P_A^*,\bar{s}_H}\right|$.

As shown in Appendix B2, Proposition 3.2 can be proved without imposing specific functional forms. The result is driven by Cournot competition and the assumption that the sensitivity of price to demand is not a function of HSR speed (i.e., $\frac{\partial(\partial P_A/\partial q_A)}{\partial\bar{s}_H}=0$). We have empirically verified Proposition 3.2 in Section 3.6.

We next examine how the substitutability of airlines and HSR moderate the HSR speed effect on airlines. Taking derivative of Eq. (3.12) with respect to γ, we obtain Eq. (3.17):

$$\frac{\partial\left|\varepsilon_{q_A,\bar{s}_H}\right|}{\partial\gamma} = \frac{\bar{s}_H(\alpha_A-P_A)\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H}+\frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|}{\big(\alpha_A-P_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))\big)^2} > 0 \tag{3.17}$$

The positive sign indicates that the air-HSR substitutability measured by γ reinforces the HSR speed effect (vertical differentiation) on airlines, no matter which quality effect (travel-time or safety) is dominant. In addition, we obtain how the elasticity of equilibrium airline traffic/price changes with γ:

$$\frac{\partial\left|\varepsilon_{q_A^*,\bar{s}_H}\right|}{\partial\gamma} = \frac{\bar{s}_H(\alpha_A-c)\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H}+\frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|}{(\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))-c)^2} > 0 \tag{3.18.1}$$

$$\frac{\partial\left|\varepsilon_{P_A^*,\bar{s}_H}\right|}{\partial\gamma}=\frac{\bar{s}_H(cN+\alpha_A)\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H}+\frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|}{(Nc+\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S})))^2}>0 \tag{3.18.2}$$

It can also be shown that $\frac{\partial\left|\varepsilon_{q_A^*,\bar{s}_H}\right|}{\partial\gamma}-\frac{\partial\left|\varepsilon_{P_A^*,\bar{s}_H}\right|}{\partial\gamma}>0$ in Appendix B3. Combining with Eq. (3.17), Eq. (3.18.1) and Eq. (3.18.2), we have Proposition 3.3.

Proposition 3.3: *With quadratic utility function, the magnitude of the elasticities of airline traffic and price with respect to HSR speed increases with air-HSR substitutability γ. γ has larger impact on the elasticity of airline traffic with respect to HSR speed than on the elasticity of airline price with respect to HSR speed.*

Lastly, we examine how the number of airlines moderates the HSR speed effect. The comparative statics of the equilibrium results with respect to the inter-airlines competition, measured by the number of airlines N, are given in Eq. (3.19.1)-Eq. (3.19.3):

$$\frac{\partial q_{i,A}^*}{\partial N}=-\frac{\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))-c}{(1-\gamma^2)(1+N)^2}<0 \tag{3.19.1}$$

$$\frac{\partial q_A^*}{\partial N}=\frac{\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))-c}{(1-\gamma^2)(1+N)^2}>0 \tag{3.19.2}$$

$$\frac{\partial P_A^*}{\partial N}=-\frac{\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S}))-c}{(1+N)^2}<0 \tag{3.19.3}$$

Eq. (3.19.1)-Eq. (3.19.3) show that the equilibrium total airline traffic increases with the number of competing airlines N, but the equilibrium airline price and equilibrium individual airline traffic decrease with N. By taking derivative of $\varepsilon_{P_A^*,\bar{s}_H}$ with respect to N, we obtain Eq. (3.20), which can be directly signed. As from Eq. (3.15.1), $\varepsilon_{q_A^*,\bar{s}_H}$ is not a function of N. Proposition 3.4 is reached.

$$\frac{\partial\left|\varepsilon_{P_A^*,\bar{s}_H}\right|}{\partial N}=\frac{-c\bar{s}_H\gamma\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H}+\frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|}{(Nc+\alpha_A-\gamma(\alpha_H-P_H-(\mathcal{T}+\mathcal{S})))^2}<0 \tag{3.20}$$

Proposition 3.4. *With quadratic utility function, the elasticity of airline price with respect to HSR speed decreases with the level of inter-airlines competition measured by the number of competing airlines N.*

Proposition 3.4 suggests that the HSR speed effect on equilibrium airline price can be negatively moderated by the inter-airlines competition. However, the elasticity of equilibrium airline traffic to HSR speed, $\varepsilon_{q_A^*,\bar{s}_H}$, is not a function of N. Thus, the inter-airlines competition does not affect $\varepsilon_{q_A^*,\bar{s}_H}$.

It should also be cautioned that in the above discussion we assume the number of airlines N is exogenous to the HSR speed change. This might be true when the HSR speed variation is small, thus not triggering airlines' entry and exit. To endogenize the number of airlines and the degree of collusion, more sophisticated airline entry model is called for.

3.5 Empirical Methodology and Data

In this section, we empirically quantify the HSR speed effect on airlines and verify our analytical findings through the natural experiment of HSR speed reduction in China. A DID method is adopted to compare airline market outcomes between the treated and control groups, both before and after the HSR speed reduction. The treated group consists of the airline routes with the presence of HSR. The control group consists of the airline routes without HSR presence. The speed effect is detected by the exogenous HSR speed reduction and the resultant variation in HSR competition effect on airlines.

The analytical model derives the impact of air-HSR service substitutability on HSR speed effect (Proposition 3.3). We thus specify the airline traffic and price equations in Eq. (3.21), which is in a log-linear form that allows nonlinear airline traffic and price functions, while guaranteeing easy identification of elasticities of airline traffic and price with respect to HSR speed (e.g., Borenstein,

1989; Schipper et al., 2002). The subscript i represents the route, and t represents the quarter and the year of the observation.

$$\begin{aligned}\ln q_{it}^{*} = \alpha_0 + \alpha_1 \times f(s_{it}) \times HSR_{it} + \alpha_2 \frac{1}{Post\_accident_{it}} \times HSR_{it} + \alpha_3 \ln Dist\_Air_{\mathrm{i}} \\ + \alpha_4 \ln HHI_{it} + \alpha_5 \ln Pop_{it} + \alpha_6 \ln Income_{it} + \alpha_7 LCC_{it} \\ + \alpha_8 Tourism_{it} + \alpha_9 Spring_t + \alpha_{10} Summer_t + \alpha_{11} Autumn_t + \alpha_{12} Year_t \\ + \alpha_{13} HSR_{it} + \psi_i + \xi_{it} \end{aligned} \tag{3.21}$$

$$\begin{aligned}\ln P_{it}^{*} = \beta_0 + \beta_1 \times f(s_{it}) \times HSR_{it} + \beta_2 \frac{1}{Post\_accident_{it}} \times HSR_{it} + \beta_3 \ln Dist\_Air_i + \beta_4 \ln HHI_{\mathrm{it}} \\ + \beta_5 \ln Pop_{it} + \beta_6 \ln Income_{it} + \beta_7 LCC_{it} + \beta_8 Tourism_{it} + \beta_9 Spring_t \\ + \beta_{10} Summer_t + \beta_{11} Autumn_t + \beta_{12} Year_t + \beta_{13} HSR_{it} + \tau_i + \nu_{it}\end{aligned}$$

where

- q_{it}^{*} is the number of airline passengers on route i at time t;
- P_{it}^{*} is the average airline yield on route i at time t;
- HSR_{it} is a dummy variable equaling to one if HSR is present on route i at time t;
- s_{it} is HSR speed on route i at time t;
- $Post\_Accident_{it}$ is the number of quarters after the 7.23 rear-ending accident;
- $Dist\_Air_i$ is the flying distance of route i;
- Pop_{it} is the geometric average population of the endpoint cities of route i at time t;
- $Income_{it}$ is the geometric average income per capita of the endpoint cities of route i at time t;
- $Tourism_i$ is the dummy variable to indicate the tourism status of route i;
- $Spring_t$, $Summer_t$, and $Autumn_t$ are the quarter dummy variables;
- HHI_{it} is the Herfindahl-Hirschman index, which captures the inter-airlines competition, on route i at time t;
- LCC_{it} is the dummy variable which indicates low-cost carrier (LCC) presence on route i at time t;
- $Year_t$ is the yearly dummy variable.

To capture the HSR speed effect on airlines, we introduce a term $f(s_{it}) \times HSR_{it}$, where $f(s_{it})$ is a function of the HSR speed s_{it}, and HSR_{it} is a dummy variable of HSR presence on this route. The interaction term $f(s_{it}) \times HSR_{it}$ measures HSR speed effect on airline traffic and price. HSR speed reduction led to variation in HSR speed, resulting in variation in air-HSR competition intensity on the treated routes. This is reflected in the term $f(s_{it}) \times HSR_{it}$, enabling us to identify the HSR speed effect. For $f(s_{it})$, we have tried alternative functional forms: s_{it}, ${s_{it}}^2$, $\sqrt{s_{it}}$.

Since the control group is not subject to HSR competition, the route-specific fixed effect is controlled for possible heterogenous characteristics between the treated and control routes. The fixed effect of the treated routes is controlled by the dummy variable HSR_{it}. The DID method is applied to compare the differences in airline traffic and price between the control and the treated airline routes before and after the HSR speed reduction. The fixed effect also controls other time-invariant variables on the route-level. The route distance is thus controlled by the route fixed effect, such that the HSR travel time variation due to the speed reduction is captured through the change in HSR speed variable $f(s_{it})$. It is also noted that, in the empirical model, we are able to disentangle the speed effect from the travel-time and safety sides because these two effects are confounding. Therefore, the estimation on the HSR speed variation should be interpreted as the "net HSR speed effect", which depends on the relative dominance of the travel time and safety effects suggested by the analytical model.

With the above specification, elasticities of airline traffic and price with respect to HSR speed can be calculated as follows. Table 3.1 summarizes the expressions of the elasticities with alternative functional forms of $f(s_{it})$.

$$\begin{aligned} \varepsilon_{q_A^*,s_H} &= \frac{\partial \ln q_{it}^*}{\partial \ln s_{it}} = \frac{\partial \ln q_{it}^*}{\partial s_{it}} \times s_{it} = \alpha_1 \times f'(s_{it}) \times s_{it} \\ \varepsilon_{p_A^*,s_H} &= \frac{\partial \ln p_{it}^*}{\partial \ln s_{it}} = \frac{\partial \ln p_{it}^*}{\partial s_{it}} \times s_{it} = \beta_1 \times f'(s_{it}) \times s_{it} \end{aligned} \tag{3.22}$$

Table 3.1 Expressions of elasticities to HSR speed with assumed forms of $f(s_{it})$

$f(s_{it})$	s_{it}	${s_{it}}^2$	$\sqrt{s_{it}}$
$\varepsilon_{q_A^*,s_H}$	$\alpha_1 s_{it}$	$2\alpha_1 {s_{it}}^2$	$\frac{1}{2}\alpha_1\sqrt{s_{it}}$
$\varepsilon_{p_A^*,s_H}$	$\beta_1 s_{it}$	$2\beta_1 {s_{it}}^2$	$\frac{1}{2}\beta_1\sqrt{s_{it}}$

In Eq. (3.21), we also include a term $\frac{1}{Post\_accident_{it}} \times HSR_{it}$ to capture passengers' immediate but short-term panic of 7.23 rear-ending accident. Such short-term panic can shift travel demand from HSR to airlines. This suggests a positive α_2 in the airline traffic volume equation, and positive β_2 in airline price equation. We assume the panic effect is proportional to the reciprocal of the number of periods post the accident, similar to the approach by Ito and Lee (2005) which captures the panic after the 911 event.[41] Other explanatory variables include the route flying distance, population, income, tourism, airline market HHI index, and LCC presence dummies. The error terms consist of a time-invariant route specific fixed effect ψ_i and τ_i, and white noise ξ_{it} and ν_{it}. Fixed-effect model is used to control potential correlation between these time-invariant error terms and the explanatory variables.

The Eq. (3.21) are in reduced-form as we express the airline traffic and price by all the exogenous variables from airline demand and supply (airlines competition) side. This is to measure the HSR speed effect on the market equilibrium airline traffic and price. In addition, we can specify the airline demand and price equations in the structural approach, where airline demand is a function of price and airline price is a function of airline demand. The system equations of airline demand and price and the estimation results will be discussed in Appendix B4.

We collect route-level airline price and traffic data for China's Big Three full service carriers namely, Air China, China Eastern, and China Southern Airlines, from January 2010 to June 30,

[41] For example, within the first period post the accident, the percentage change on the airline yield is calculated as $e^{\beta_2} - 1$. Let us assume the airline yield is P_1 when $Post\_accident_{it} = 1$, and the airline yield is P_0 without the accident. Thus $\frac{P_1 - P_0}{P_0} = \frac{P_1}{P_0} - 1 = e^{\beta_2} - 1$. Similarly, in the *n*-th period post the accident, the percentage change on airline yield is $e^{\beta_2/n} - 1$, and this term converges to zero when *n* is increasing.

2013, a total of 14 quarters. These three airlines are the largest in China, and dominate market with more than 80% of total domestic traffic (Zhang et al., 2014). The sample period covers observations prior to and post the HSR speed reduction occurred on July 1, 2011 and August 28, 2011, as well as the 7.23 rear-ending accident on July 23, 2011.

A total of 74 routes are included in our sample, including the ones linking Beijing, Shanghai and Guangzhou to all the provincial capital cities in China, except Lhasa.[42] Among the 74 airline routes, HSR is present on 9 routes that all experienced the HSR speed reduction in Quarter 3 of 2011. The description of these 9 routes can be found in Table 3.2. The 9 routes compose our treated group, with the other 65 routes as control group. As these sample routes are the ones linking three Chinese airline hubs (Beijing, Guangzhou and Shanghai) with major Chinese cities, the controlled and treated routes have similar characteristics, such as passenger volume, route distance, airport size etc.

[42] We exclude the origin-destination (OD) routes along the Beijing-Shanghai HSR line which opened on July 1st 2011, because this HSR line opened at the same time of the speed reduction. The maximum design speed of this line is 380 km/hr, but it only allows to operate at a maximum speed of 300 km/hr. Thus, there is no direct comparison of the outcomes before and after the HSR speed reduction for these routes, which make the route not suitable for the DID estimation.

Table 3.2 Summary of the treated routes before and after the HSR speed reduction

Route	HSR Route Distance (km)	Date of speed reduction	Speed before reduction	Speed after reduction	HSR in-Vehicle Travel Time (mins)	HSR Total Travel Time (mins)
Shanghai-Hefei	456	28-Aug, 2011	233	186	128	202
Beijing-Taiyuan	513	28-Aug,2011	250	200	152	242
Shanghai-Zhengzhou	651	28-Aug,2011	250	200	239	318
Guangzhou-Changsha	726	01-Jul,2011	350	300	137	225
Shanghai-Wuhan	826	28-Aug,2011	240	192	260	355
Shanghai-Fuzhou	883	28-Aug,2011	250	200	264	346
Guangzhou-Wuhan	995	01-Jul,2011	350	300	218	306
Shanghai-Xiamen	1109	28-Aug,2011	250	200	381	495
Guangzhou-Hefei	1427	01-Jul,2011	325	275	401	468

Notes:

1. The Shanghai-Hefei HSR line passes through Shanghai-Nanjing intercity railway segment (with design speed of 250 km/hr before the speed reduction) and Nanjing-Hefei passenger-railway segment (with design speed of 200 km/hr before the speed reduction). The HSR speed on the Shanghai-Hefei line is thus calculated by taking a weighted average based on distance of the two segments. The same applies to the lines of Shanghai-Wuhan and Guangzhou-Hefei.
2. The HSR total travel time adds the access and egress time between HSR stations and the city centers to the HSR in-vehicle time.
3. The HSR total travel time and in-vehicle time are the time after the HSR speed reduction. The HSR in-vehicle time before the HSR speed reduction was not available.

Airfare data is obtained from the Chinese Airfare Information Network. Route distance is collected from Statistical Data on Civil Aviation of China (CAAC, 2014). Each city's per capita income, population and GDP are collected from the city statistical yearbook. The list of the 25 most important tourism cities is released by Forbes China every year, using which we construct the tourism dummy variable. We define a route as a tourism route, if at least one of the endpoint airport city is one of the 25 most developed cities for tourism in mainland China, released by Forbes China every year. The data on the HSR speed, and route distance are obtained from two websites: www.12306.cn (the official online booking site for all trains in China) and www.gaotie.cn (the

website summarizing HSR information in China).[43] Our airfare and passenger volume data are available on daily basis. Given most of our control variables, such as population, income and HHI, are only available at the quarterly basis, we aggregate the daily price and traffic data into the quarterly basis. The quarterly passenger volume is the aggregate of the daily data, and the quarterly average price is calculated by dividing the quarterly aggregate airline revenue by the quarterly passenger volume. [44]

The analytical model suggests HSR speed effect varies with the intermodal substitutability. We thus divide the 9 treated routes (see Table 3.2) into two groups based on the HSR route distance: 5 short-haul routes (<850 km: Shanghai-Hefei, Beijing-Taiyuan, Shanghai-Zhengzhou, Guangzhou-Changsha), and 4 medium-to-long-haul routes (>850 km: Shanghai-Fuzhou, Guangzhou-Wuhan, Shanghai-Xiamen, Guangzhou-Hefei). Our estimations are run for the two subsamples separately. As suggested by Proposition 3.3, it is expected to observe stronger HSR speed effect on the short-haul routes (<850 km) as air-HSR services are more substitutable. In addition, we have tried to divide the treated routes based on total HSR travel time to differentiate the air-HSR service substitutability: 4 short-haul routes (< 5 hours: Shanghai-Hefei, Beijing-Taiyuan, Guangzhou-Changsha, Guangzhou-Wuhan) and 5 medium-to-long-haul routes (>5 hours: Shanghai-Zhengzhou, Shanghai-Wuhan, Shanghai-Fuzhou, Shanghai-Xiamen, Guangzhou-Hefei), the results of which are relegated to Table B1-B3 of Appendix B.

Before formal estimation, we plot average quarterly airline traffic and yield for both treated and control group (see Figure 3.1). [45] The accident and HSR speed reduction occurred at the 7th quarter (the season 7) of the sample period. The figure clearly shows that our treated and control groups have a common time trend before HSR speed reduction, satisfying the DID requirement. As shown in Figure 3.1 (a), airline traffic increased significantly post HSR speed reduction on the treated

[43] The two websites are in Chinese language.

[44] When calculating the average ticket price and air traffic, we removed the observations of "first-class" and "business-class", to focus on airline demand and price of the "economy class" observations.

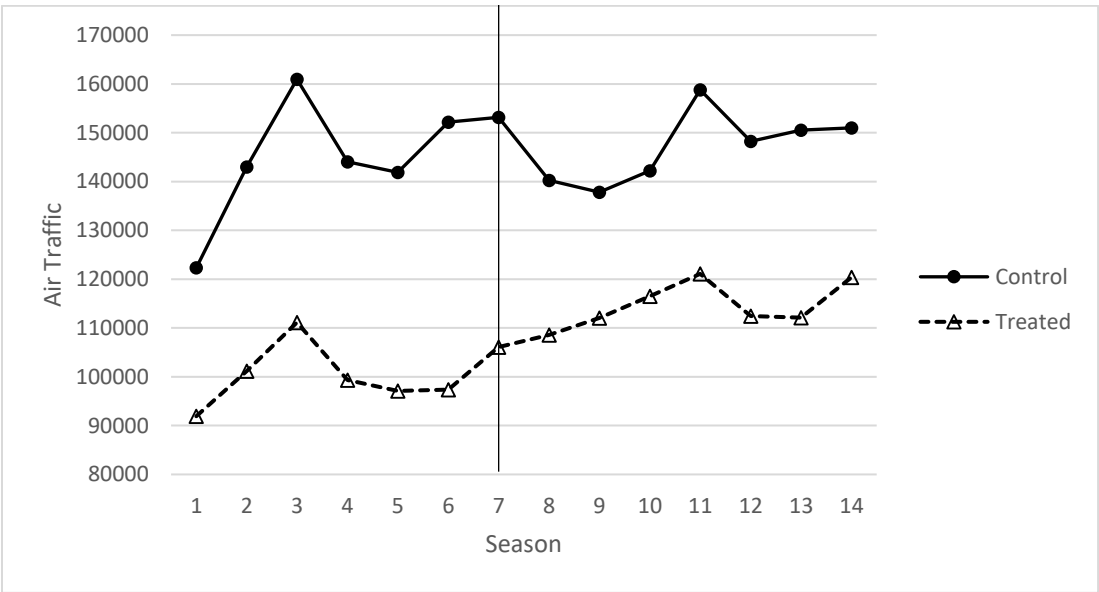
[45] The airline yield is calculated by dividing the airfare by the flying distance. The average yield of each route for the treated and control groups is calculated using each airline's passenger volume as the weight on the route.

routes. [46] For airline price in Figure 3.1 (b), the HSR speed effect is much less obvious. But between the 9th and 14th quarter, airline yield on the treated routes seems less volatile and did not plummet as the control group did. This may indicate a positive effect of HSR speed reduction on airfare. In Figure 3.2, we further distinguish observations for the two subsamples of treated group: routes shorter, or longer than 850 km. The airline traffic on the routes shorter than 850 km increases more significantly than that on the routes longer than 850 km does. This may suggest stronger HSR speed effect on short-haul routes when airline and HSR services are more substitutable. For the airline yield, no clear change is observed post the speed reduction.

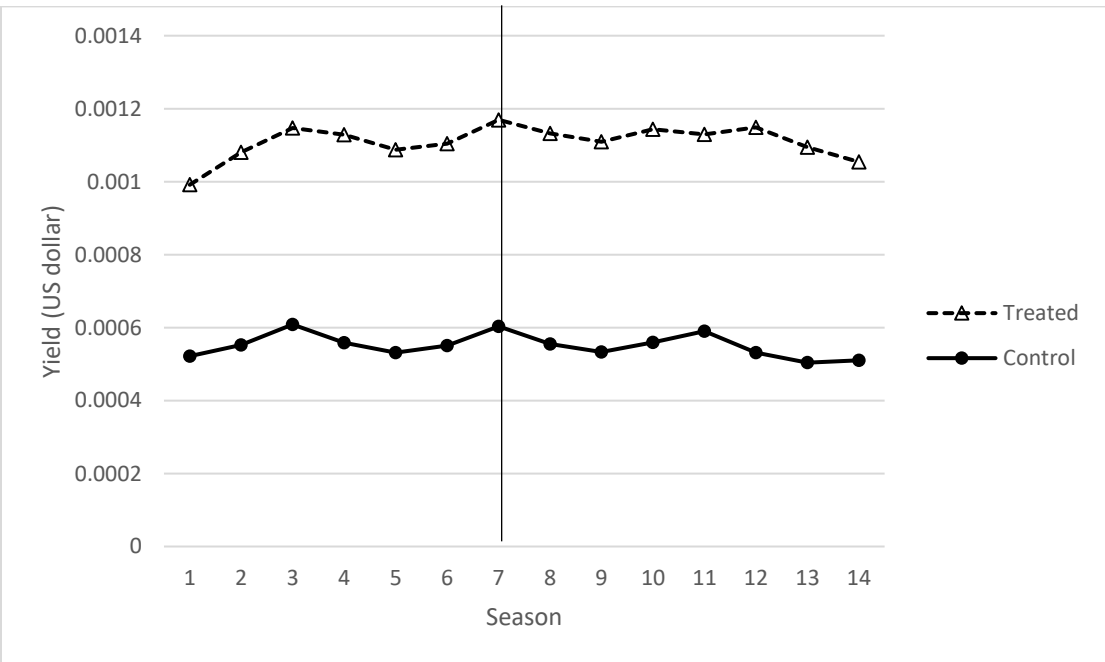
[46] There is a drop of airline traffic for the control routes after Quarter 3 of 2011, which was when the speed reduction occurred. This traffic drop is purely due to the seasonal cycle of air travel demand in China. Quarter 3 of 2011, i.e. the summer season, is the peak air travel period in China, whereas the demand is much weaker in the following winter season, i.e., Quarter 4. Therefore, without the HSR speed reduction, the airline traffic in the control group routes dropped at Quarter 4.

Figure 3.1 Evolution of airline traffic and yield for the treated (HSR) and control (no HSR) routes (quarterly data from Quarter 1 of 2010 to Quarter 3 of 2013)

(a). Airline traffic



(b). Airline yield

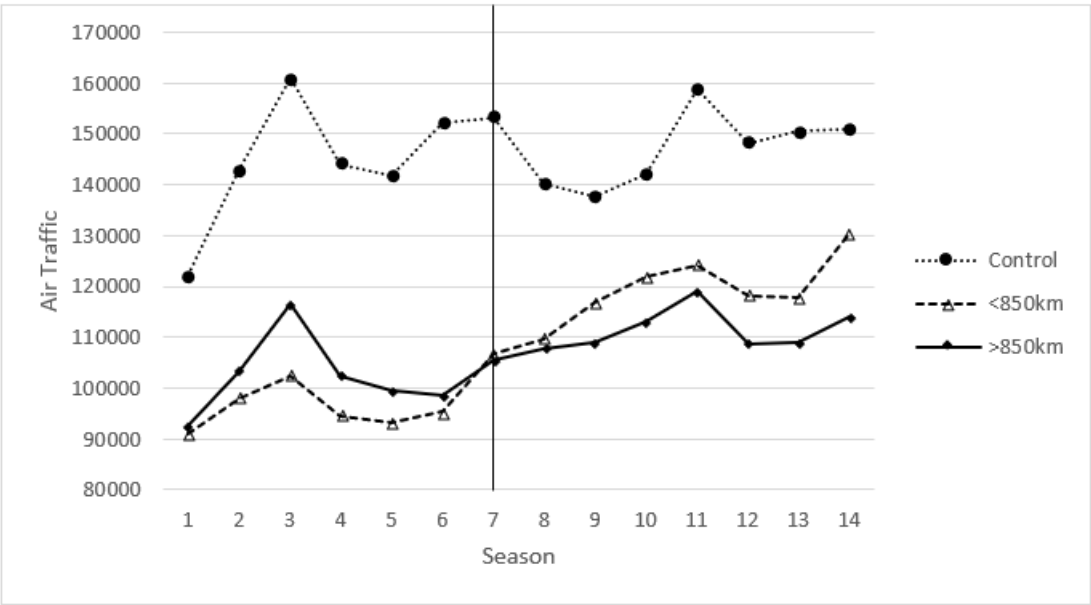


Note: the vertical lines represent the time of speed reduction.

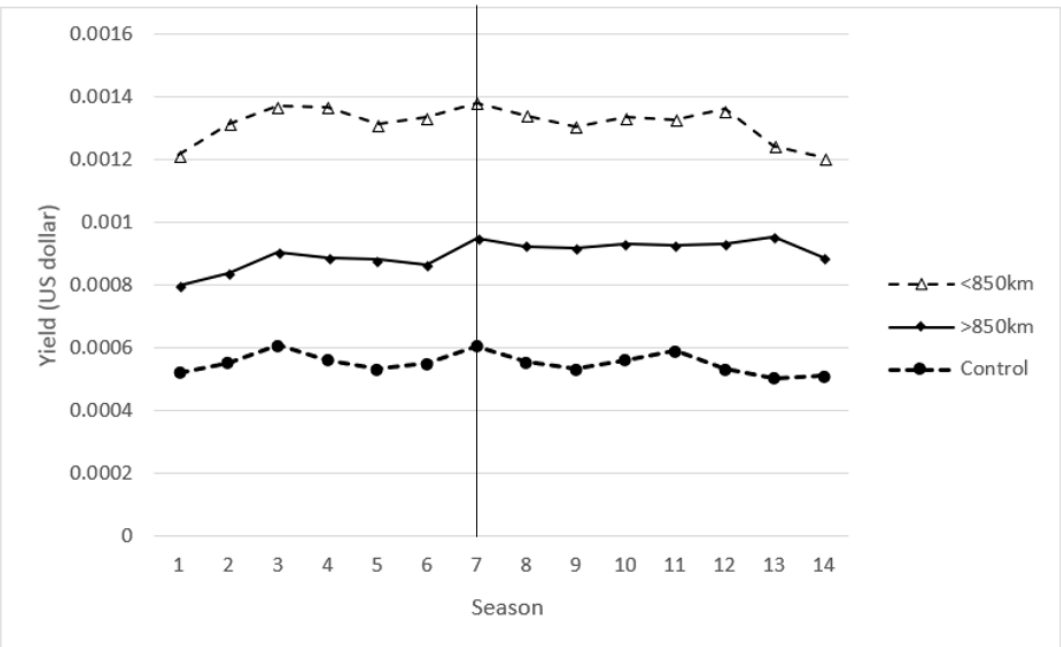
Figure 3.2 Evolution of airline traffic and yield for treated routes shorter and longer than 850 km and control (no HSR) routes

(quarterly data from Quarter 1 of 2010 to Quarter 3 of 2013)

(a). Airline traffic



(b). Airline yield



Note: the vertical lines represent the time of speed reduction.

3.6 Empirical Results

Estimation results of Eq. (3.21) are summarized in Table 3.3 and 3.4 with alternative functional forms of the HSR speed variable ($f(s_{it})$= s_{it}, ${s_{it}}^2$, $\sqrt{s_{it}}$). The estimations are based on full treated sample, the treated routes shorter than 850 km and longer than >850 km. The HSR speed reduction overall has statistically significant and positive effect on airline traffic and price, suggested by the negative sign of α_1 and β_1. This also implies the travel-time effect dominates safety effect of HSR speed in China. In addition, HSR speed effect manifests on treated routes shorter than 850 km, while not identified on longer than 850 km treated routes. This empirical finding confirms our Proposition 3.3 that HSR speed effect is stronger on short-haul routes when airline and HSR services are more substitutable. Robustness tests have also been done using different distance thresholds to divide sample treated routes, for example, routes shorter or longer than 700 km, 950 km etc. The estimations are qualitatively consistent: the HSR speed effect is only statistically significant on short-haul treated group. In addition, we have tried estimation on subsample treated routes based on the HSR travel time to differentiate the air-HSR service substitutability (shorter vs. longer than 5-hour HSR travel time). The estimation results are collated in Table B1-B3 of Appendix B. It is noted that we obtained very similar estimation results as dividing the treated routes based on distance: the HSR speed effect is only statistically significant on the short-haul routes with total HSR travel time less than 5 hours.

Table 3.3 Estimation results for airline traffic equation with $f(s_{it}) = s_{it}, s_{it}^2$, or $\sqrt{s_{it}}$

Airline Traffic	All	<850km	>850km	All	<850km	>850km	All	<850km	>850km
	$f(s_{it}) = s_{it}$			$f(s_{it}) = s_{it}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
α_1	-0.0035***	-0.0042***	0.0100	-5.51×10^{-6}***	-6.42×10^{-6}***	-1.84×10^{-5}	-0.119***	-0.144***	-0.073**
	(0.001)	(0.0008)	(0.046)	(-2.24×10^{-7})	(-1.67×10^{-6})	(7.99×10^{-5})	(0.039)	(0.028)	(0.0308)
α_2	1.159	1.245	1.227	1.098	1.238	1.216	1.179	1.247	1.219
	(5.755)	(3.439)	(4.051)	(5.746)	(3.452)	(4.058)	(5.758)	(3.437)	(0.314)
HHI	-0.095**	-0.090**	-0.096**	-0.092**	-0.089**	-0.1005**	-0.096**	-0.090**	-0.102**
	(0.046)	(0.044)	(0.045)	(0.047)	(0.045)	(0.045)	(0.046)	(0.044)	(0.045)
Population	-1.035	-0.839	-0.254	-1.076	-0.939	-0.317	-0.997	-0.773	-0.360
	(0.717)	(0.662)	(0.714)	(0.722)	(0.666)	(0.709)	(0.714)	(0.661)	(0.710)
Income	-0.285**	-0.361***	-0.367***	-0.283	-0.370***	-0.331	-0.285***	-0.355***	-0.324**
	(0.136)	(0.129)	(0.130)	(0.137)	(0.130)	(0.130)	(0.136)	(0.129)	(0.130)
LCC	-0.027	-0.027	-0.027	-0.027	-0.027	-0.026	-0.027	-0.027	-0.026
	(0.065)	(0.064)	(0.063)	(0.065)	(0.064)	(0.063)	(0.065)	(0.063)	(0.063)
Tourism	0.007	0.026	0.061	0.006	0.013	0.087*	0.006	0.030	0.090
	(0.050)	(0.043)	(0.046)	(0.051)	(0.043)	(0.047)	(0.050)	(0.043)	(0.047)
Spring	0.717***	-0.240***	0.687***	0.719***	-0.243***	0.698***	0.716***	-0.237	-0.225***
	(0.246)	(0.044)	(0.239)	(0.246)	(0.044)	(0.238)	(0.245)	(0.044)	(0.044)
Summer	0.205	0.199	0.193	0.206	0.198	0.196	0.204	0.199	0.196
	(0.165)	(0.162)	(0.161)	(0.166)	(0.163)	(0.160)	(0.165)	(0.162)	(0.160)
Autumn	0.333**	-0.610***	0.319**	0.335**	-0.612***	0.322**	0.332**	-0.608***	-0.602***
	(0.168)	(0.160)	(0.163)	(0.168)	(0.161)	(0.163)	(0.168)	(0.160)	(0.158)
Year2011	0.149***	0.153***	0.145***	0.150***	0.156***	0.141***	0.149***	0.151***	0.141***
	(0.030)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)
Year2012	0.837***	0.840***	0.820***	0.838***	-0.094	0.817	0.836***	0.836***	0.818***
	(0.164)	(0.161)	(0.160)	(0.164)	(0.165)	(0.159)	(0.164)	(0.161)	(0.159)
Year2013	0.348***	0.357***	0.335***	0.350***	0.363***	0.328***	0.347***	0.353***	0.328***
	(0.043)	(0.041)	(0.042)	(0.043)	(0.041)	(0.042)	(0.043)	(0.041)	(0.042)
Constant	20.600***	20.942***	15.951***	20.820***	21.573***	16.215***	20.417***	20.611***	18.515***

Airline Traffic	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**
	$f(s_{it}) = s_{it}$			$f(s_{it}) = {s_{it}}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
	(4.529)	(4.197)	(4.762)	(4.562)	(4.223)	(4.499)	(4.515)	(4.189)	(4.539)
Time trend fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
HSR route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Observations	1,036	980	966	1,036	980	966	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_{\mathrm{i}}$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
2. ***<0.01, **<0.05, *<0.10.
3. Standard errors are in parentheses.

Table 3.4 Estimation results for airline price equation with assumed functional forms of $f(s_{it}) = s_{it}, s_{it}^2$, or $\sqrt{s_{it}}$

Airline price	All	<850km	>850km	All	<850km	>850km	All	<850km	>850km
	$f(s_{it}) = s_{it}$			$f(s_{it}) = s_{it}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
β_1	-0.0008**	-0.0016***	-0.0217	-1.64× 10^{-6}*	-3.11× 10^{-6}***	-6.46× 10^{-7}	-0.028*	-0.049***	0.225
	(0.0004)	(0.0003)	(0.0189)	(9.02× 10^{-7})	(6.71× 10^{-7})	(3.27× 10^{-6})	(0.05)	(0.011)	(1.24)
β_2	-0.034	-0.023	0.031	-0.037	-0.033	0.032	-0.038	-0.013	0.020
	(0.051)	(0.031)	(0.037)	(0.060)	(0.043)	(0.037)	(0.062)	(0.031)	(0.022)
HHI	0.1120***	0.1036***	0.106***	0.116***	0.104***	0.108***	0.116***	0.103***	0.108***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Population	0.811***	0.641***	0.847***	0.881***	0.592**	0.895***	0.916***	0.663***	0.906***
	(0.277)	(0.267)	(0.292)	(0.290)	(0.267)	(0.290)	(0.288)	(0.267)	(0.290)
Income	0.081	0.094*	0.098*	0.085	0.088*	0.084	0.085	0.096*	0.083
	(0.054)	(0.052)	(0.053)	(0.055)	(0.052)	(0.053)	(0.055)	(0.052)	(0.053)
LCC	0.0042	0.003	0.003	0.004	0.003	0.0032	0.004	0.003	0.003
	(0.0261)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)
Tourism	0.0049	0.005	-0.0014	0.004	0.003	-0.008	0.002	0.004	-0.008
	(0.0199)	(0.0174)	(0.019)	(0.020)	(0.017)	(0.019)	(0.020)	(0.017)	(0.019)
Spring	-0.0371**	-0.034*	0.407***	0.409***	-0.036**	0.403***	0.408***	-0.033*	-0.035**
	(0.0183)	(0.0178)	(0.097)	(0.099)	(0.017)	(0.097)	(0.099)	(0.017)	(0.018)
Summer	0.170**	0.167**	0.168***	0.173***	0.167**	0.167***	0.173***	0.167***	0.167**
	(0.066)	(0.065)	(0.065)	(0.066)	(0.065)	(0.065)	(0.066)	(0.065)	(0.065)
Autumn	-0.187***	-0.189***	0.253***	0.258***	-0.190***	0.252***	0.258***	-0.188***	-0.185***
	(0.065)	(0.064)	(0.066)	(0.067)	(0.064)	(0.066)	(0.067)	(0.064)	(0.064)
Year2011	0.0127	0.013	0.010	0.011	0.014	0.012	0.011	0.012	0.012
	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)
Year2012	-0.213***	0.234***	0.226***	0.227***	-0.207***	0.226***	0.226***	0.233***	0.226***
	(0.067)	(0.065)	(0.065)	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)	(0.065)
Year2013	-.0515***	-0.0491***	-0.057***	-0.054***	-0.046***	-0.054***	-0.055***	-0.050***	-0.055***
	(0.017)	(0.016)	(0.0172)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
Constant	-7.143***	-6.025***	-7.418***	-8.135***	-5.690***	-8.107***	-8.340***	-6.147***	-8.101***

Airline price	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**
		$f(s_{it}) = s_{it}$			$f(s_{it}) = {s_{it}}^2$			$f(s_{it}) = \sqrt{s_{it}}$	
	(1.752)	(1.693)	(1.945)	(1.695)	(1.840)	(1.837)	(1.822)	(1.695)	(1.858)
Time trend fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
HSR route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Observations	1,036	980	966	1,036	980	966	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_{\mathrm{i}}$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
2. ***<0.01, **<0.05, *<0.10.
3. Standard errors are in parentheses.

Table 3.5 collates the estimated elasticities and percent changes in airline traffic and price to HSR speed reduction. On shorter than 850 km routes, our HSR speed effect estimates seem robust with assumption on $f(s_{it})$. The estimates are conducted for 250 km/hr HSR and 350 km/hr HSR respectively. Specifically, for shorter than 850 km routes, with 250 km/hr HSR, the elasticities of airline traffic and price to HSR speed are estimated to be -0.802 to -1.13, and -0.38 to -0.4, respectively. HSR speed dropped by 20% from 250 km/hr to 200 km/hr. HSR speed reduction thus increased airline traffic and price by 16% to 22%, and 7.6% to 8%, respectively. When HSR speed is 350 km/hr, elasticities of airline traffic and price to HSR speed are larger than those of 250 km/hr speed HSR. HSR speed dropped by 14.3% from 350 km/hr to 300 km/hr. HSR speed reduction increased airline traffic and price by 21% to 22% and 5.7% to 10.8% on the 350 km/hr HSR routes. With the estimated HSR speed effect, we are also able to construct the estimate on HSR entry effect on airlines. The percentage change of airline traffic and price before and after a HSR entry can be calculated as $\frac{q_{it}^{*}|\,HSR=1-\,q_{it}^{*}|HSR=0}{q_{it}^{*}|\,HSR=0} = e^{\alpha_1 \times f(s_{it})} - 1$, and $\frac{P_{it}^{*}|\,HSR=1-\,P_{it}^{*}|HSR=0}{P_{it}^{*}|\,HSR=0} = e^{\beta_1 \times f(s_{it})} - 1$. It can be seen, for routes shorter than 850 km, HSR entry can cause more dramatic decrease in airline traffic and price, similar to the findings in Wan et al. (2016).

Table 3.5 Estimated HSR speed effect with assumed functional forms of $f(s_{it}) = s_{it}, {s_{it}}^2$, or $\sqrt{s_{it}}$

(a) For 250 km/hr HSR lines

		<850 km		
$f(s_{it})$		s_{it}	${s_{it}}^2$	$\sqrt{s_{it}}$
Elasticity to HSR speed	$\varepsilon_{q_A^*, s_H}$	-1.05	-0.802	-1.13
	$\varepsilon_{p_A^*, s_H}$	-0.40	-0.38	-0.38
Impact of HSR speed reduction	Traffic Change %	21%	16%	22%
	Price Change %	8%	7.6%	7.6%
Impact of HSR entry	Traffic Change %	-65%	-33%	-89%
	Price Change %	-33%	-18%	-54%

Note: For >850 km routes, the items for the functional form s_{it} and ${s_{it}}^2$ are not calculated, because the coefficients of the HSR speed variables are not statistically significant.

(a) For 350 km/hr HSR lines

		<850 km		
$f(s_{it})$		s_{it}	${s_{it}}^2$	$\sqrt{s_{it}}$
Elasticity to HSR speed	$\varepsilon_{q_A^*,s_H}$	-1.47	-1.57	-1.44
	$\varepsilon_{p_A^*,s_H}$	-0.56	-0.76	-0.411
Impact of HSR speed reduction	Traffic Change %	21%	22%	21%
	Price Change %	5.7%	10.8%	5.8%
Impact of HSR entry	Traffic Change%	-71%	-54%	-90%
	Price Change %	-43%	-32%	-93%

Note: For >850 km routes, the items for the functional form s_{it} and ${s_{it}}^2$ are not calculated, because the coefficients of the HSR speed variables are not statistically significant.

The estimates of other coefficients seem to be reasonable. First, the airline traffic is higher when airline market is less concentrated, since airline competition can reduce the airline price. Second, the airline price increases with the market population and income level. In addition, the short-run accident effect is, however, not identified (i.e., the estimated α_2 and β_2 are statistically insignificant). This is probably because the accident effect could attenuate fast over time, most likely within the quarter in which it occurred. Our quarterly data thus cannot accurately capture it. Since our ticket data is for the flights departing on particular day, not the booking price on that day, some observations after the accident could be the tickets booked before the event, thus confounding the accident effect estimation. Wei et al. (2017) find significant short-term panic effect: the airline price rose by 27.4% immediately within the first half month after the accident. This is because they only examined a very short-term period. And their ticket information is for the booking on each day, not the tickets flying on the day.[47] The coefficients of LCC variable are insignificant in both the airline traffic and price equations. This is because the LCCs penetration in China is still very low, with less than 10% of market share (Fu et al., 2015; Wang et al., 2018). Fu et al. (2015a) and Wang et al. (2018) find that LCCs have little impact on the route average ticket price and traffic.

[47] The estimated coefficient for the $Tourism_{it}$ is insignificant. This is probably because the list of top 25 most developed tourism cities by Forbes China has not been changed significantly from 2010 to 2012, thus the values of $Tourism_{it}$ on each route does not change significantly over time. As we have controlled the route-level fixed effect, the coefficients for the relatively time-invariant variables cannot be significantly identified.

It is somewhat surprising to obtain a statistically insignificant coefficient estimate on population variable and a statistically significant and negative coefficient estimation on the average personal income variable in our airline traffic and price equations. This result is likely to be driven by our sample route selection criteria, which consider the routes linking Beijing, Shanghai, and Guangzhou with provincial capital cities of China. Many provincial capital cities, e.g., Chengdu, Xi'an, Kunming, are in western and central China, with lower population and lower average personal income. However, these cities are relatively geographically remote to the economic centers, i.e., Beijing, Shanghai and Guangzhou, thus relying heavier upon air transport to be linked. Moreover, despite the lower average personal income, the income disparities in such cities are higher than Beijing, Shanghai and Guangzhou. As air travel is consumed by the population group with high income, the share of population traveling by air can be higher in these cities compared to cities with higher average personal income. The estimates of the quarterly and yearly dummies suggest that summer is the peak season of the air travel in China, and air traffic and price increase over years.

HSR speed effects are only statistically significant on treated routes shorter than 850 km or shorter than 5-hour HSR travel time (Table B1-B3 of Appendix B), which supports our Proposition 3.3 that air-HSR substitutability reinforces the HSR speed effect. To directly account for the different degree of air-HSR substitutability for different route distance, we construct a term $h(s_{it}, D_i) \times HSR_{it}$, as specified in Eq. (3.23), to allow HSR speed effect to decrease with route distance D_i. Specifically, we try $\frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ and $\sqrt{\frac{s_{it}}{D_i}}$ for $h(s_{it}, D_i)$. In this way, the HSR speed effect could be negatively moderated by the HSR route distance as an indicator of air-HSR service substitutability.

$$\begin{aligned}\ln q_{it}^{*} = \alpha_0 + \alpha_1 \times h(s_{it}, D_i) \times HSR_{it} + \alpha_2 \frac{1}{Post\_accident_{it}} \times HSR_{it} + \alpha_3 \ln Dist\_Air_{\mathrm{i}} \\ + \alpha_4 \ln HHI_{it} + \alpha_5 \ln Pop_{it} + \alpha_6 \ln Income_{it} + \alpha_7 LCC_{it} \\ + \alpha_8 Tourism_{it} + \alpha_9 Spring_t + \alpha_{10} Summer_t + \alpha_{11} Autumn_t + \alpha_{12} Year_t \\ + \alpha_{13} HSR_{it} + \psi_i + \xi_{it}\end{aligned} \tag{3.23}$$

$$\ln P_{it}^{*} = \beta_0 + \beta_1 \times h(s_{it}, D_i) \times HSR_{it} + \beta_2 \frac{1}{Post\_accident_{it}} \times HSR_{it} + \beta_3 \ln Dist\_Air_i$$
$$+ \beta_4 \ln HHI_{\mathrm{it}} + \beta_5 \ln Pop_{it} + \beta_6 \ln Income_{it} + \beta_7 LCC_{it}$$
$$+ \beta_8 Tourism_{it} + \beta_9 Spring_t + \beta_{10} Summer_t + \beta_{11} Autumn_t + \beta_{12} Year_t$$
$$+ \beta_{13} HSR_{it} + \tau_i + \nu_{it}$$

The elasticities of airline traffic and price to HSR speed can be derived as follows:

$$\varepsilon_{q_A^*, \bar{s}_H} = \frac{\partial \ln q_{it}^*}{\partial \ln s_{it}} = \frac{\partial \ln q_{it}^*}{\partial s_{it}} \times s_{it} = \alpha_1 \times h'(s_{it}, D_i) \times s_{it}$$
$$\varepsilon_{p_A^*, \bar{s}_H} = \frac{\partial \ln p_{it}^*}{\partial \ln s_{it}} = \frac{\partial \ln p_{it}^*}{\partial s_{it}} \times s_{it} = \beta_1 \times h'(s_{it}, D_i) \times s_{it} \tag{3.24}$$

The expressions of the elasticities are summarized in Table 3.6 for different forms of $h(s_{it}, D_i)$. With $h(s_{it}, D_i) = (\frac{s_{it}}{D_i})^2$, the airline traffic and price elasticities with respect to HSR speed decrease at a faster rate with an increasing HSR distance D_i or decreasing HSR speed s_{it}, while, with $h(s_{it}, D_i) = \sqrt{\frac{s_{it}}{D_i}}$, the airline traffic and price elasticities with respect to HSR speed decrease at a slower rate with an increasing HSR route distance D_i or decreasing HSR speed s_{it}.

Table 3.6 Expressions of elasticities with respect to HSR speed with assumed functional forms of $h(s_{it}, D_i) = \frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ or $\sqrt{\frac{s_{it}}{D_i}}$

$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$	$(\frac{s_{it}}{D_i})^2$	$\sqrt{\frac{s_{it}}{D_i}}$
$\varepsilon_{q_A^*, s_H}$	$\alpha_1 \frac{s_{it}}{D_i} = \frac{\alpha_1}{T_{it}}$	$2\alpha_1 \left(\frac{s_{it}}{D_i}\right)^2 = \frac{2\alpha_1}{T_{it}^2}$	$\frac{1}{2}\alpha_1 \sqrt{\frac{s_{it}}{D_i}} = \frac{1}{2}\frac{\alpha_1}{\sqrt{T_{it}}}$
$\varepsilon_{p_A^*, s_H}$	$\beta_1 \frac{s_{it}}{D_i} = \frac{\beta_1}{T_{it}}$	$2\beta_1 (\frac{s_{it}}{D_i})^2 = \frac{2\beta_1}{T_{it}^2}$	$\frac{1}{2}\beta_1 \sqrt{\frac{s_{it}}{D_i}} = \frac{1}{2}\frac{\beta_1}{\sqrt{T_{it}}}$

The estimation results of the airline traffic and price equations with the alternative functional forms of $h(s_{it}, D_i)$ are collated in Table 3.7 and 3.8. First, it is found that HSR speed reduction significantly increased airline traffic and price, suggested by the statistically significantly negative sign of α_1 and β_1. This again confirms that travel-time effect dominates the safety effect of the HSR speed on airlines.

Table 3.7 Estimation results for airline traffic equation with assumed functional forms of $h(s_{it}, D_i) = \frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ or $\sqrt{\frac{s_{it}}{D_i}}$

Airline Traffic			
$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$	$(\frac{s_{it}}{D_i})^2$	$\sqrt{\frac{s_{it}}{D_i}}$
α_1	-1.899***	-1.765***	-2.813***
	(0.437)	(0.424)	(0.612)
α_2	-0.001	0.014	-0.063
	(0.101)	(0.078)	(0.081)
HHI	-0.092**	-0.093**	-0.091**
	(0.044)	(0.044)	(0.044)
Population	-0.876	-0.946	-0.811
	(0.664)	(0.665)	(0.663)
Income	-0.352***	-0.354***	-0.351***
	(0.130)	(0.130)	(0.130)
LCC	-0.027	-0.028	-0.028
	(0.064)	(0.064)	(0.064)
Tourism	0.018	0.015	0.022
	(0.043)	(0.043)	(0.044)
Spring	-0.237***	-0.239***	-0.237***
	(0.044)	(0.044)	(0.044)
Summer	0.198	0.198	0.199
	(0.163)	(0.163)	(0.163)
Autumn	-0.609***	-0.611***	-0.608***
	(0.160)	(0.161)	(0.161)
Year2011	0.153***	0.155***	0.152***
	(0.029)	(0.030)	(0.030)
Year2012	0.840***	0.843***	0.838***
	(0.162)	(0.162)	(0.162)
Year2013	0.356***	0.360***	0.354***
	(0.041)	(0.042)	(0.041)
Constant	21.099***	21.523***	20.764***

Airline Traffic			
$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$	$(\frac{s_{it}}{D_i})^2$	$\sqrt{\frac{s_{it}}{D_i}}$
	(4.207)	(4.215)	(4.201)
Time trend fixed effect	✓	✓	✓
HSR route fixed effect	✓	✓	✓
Individual route fixed effect	✓	✓	✓
No. of Observations	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_i$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
2. ***<0.01, **<0.05, *<0.10.
3. Standard errors are in parentheses.

Table 3.8 Estimation results for airline price equation with assumed functional forms of $h(s_{it}, D_i) = \frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ or $\sqrt{\frac{s_{it}}{D_i}}$

Airline Price			
$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$	$(\frac{s_{it}}{D_i})^2$	$\sqrt{\frac{s_{it}}{D_i}}$
β_1	-0.656***	-0.580***	-0.993***
	(0.169)	(0.171)	(0.247)
β_2	-0.019	0.052*	0.022
	(0.032)	(0.031)	(0.034)
HHI	0.111***	0.103***	0.103***
	(0.017)	(0.018)	(0.018)
Population	0.551**	0.603**	0.651***
	(0.261)	(0.269)	(0.268)
Income	0.108**	0.097*	0.098*
	0.051	(0.052)	(0.052)
LCC	0.004	0.003	0.003

Airline Price			
$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$	$(\frac{s_{it}}{D_i})^2$	$\sqrt{\frac{s_{it}}{D_i}}$
	(0.025)	(0.026)	(0.026)
Tourism	-0.001	-0.0007	0.0025
	(0.017)	(0.017)	(0.017)
Spring	-0.031*	-0.034*	-0.033*
	(0.017)	(0.018)	(0.018)
Summer	0.184***	0.167**	0.168**
	(0.064)	(0.066)	(0.066)
Autumn	-0.198***	-0.189***	-0.188***
	(0.063)	(0.065)	(0.064)
Year2011	-0.038	0.014	0.012
	(0.011)	(0.012)	(0.012)
Year2012	0.245	0.235***	0.233***
	(0.064)	(0.066)	(0.065)
Year2013	-0.048	-0.048***	-0.050***
	(0.016)	(0.017)	(0.017)
Constant	-5.649	-5.854***	-6.102***
	(1.659)	(1.704)	(1.698)
Time trend fixed effect	✓	✓	✓
HSR route fixed effect	✓	✓	✓
Individual route fixed effect	✓	✓	✓
No. of Observations	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_{\mathrm{i}}$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
2. ***<0.01, **<0.05, *<0.10.
3. Standard errors are in parentheses.

We construct the elasticities estimate and the percent changes in airline traffic and price with respect to the HSR speed reduction for three categories of routes which have distinct air-HSR service substitutability: 500 km, 850 km, and 1,100 km (as shown in Table 3.9). It is found that the estimates for the 500-km route are relatively robust across different forms of $h(s_{it}, D_i)$. HSR speed

reduction raised airline traffic by 17.7% to 19.9% when HSR speed is 250 km/hr, and by 16.8% to 34.6% when HSR speed is 350 km/hr. And the airline price rose by 5.8% to 7.0% when HSR speed is 250 km/hr, and by 5.9% to 8.1% when HSR speed is 350 km/hr. When route distance is extended to 850 km and 1,100 km, the HSR speed effects decrease while the magnitudes largely depend on the specific functional form of $h(s_{it}, D_i)$.

Table 3.9 Estimated elasticities of airline price and demand to HSR speed reduction and overall HSR competition effect

(a). For 250 km/hr HSR lines

$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$			$(\frac{s_{it}}{D_i})^2$			$\sqrt{\frac{s_{it}}{D_i}}$		
Route Distance	500 km	850 km	1100 km	500 km	850 km	1100 km	500 km	850 km	1100 km
$\varepsilon_{q_A^*, s_H}$	-0.95	-0.56	-0.43	-0.88	-0.31	-0.18	-0.99	-0.76	-0.67
$\varepsilon_{p_A^*, s_H}$	-0.33	-0.19	-0.15	-0.29	-0.10	-0.06	-0.35	-0.27	-0.24
Traffic Change %	19.0%	11.2%	8.6%	17.7%	6.1%	3.6%	19.9%	15.3%	13.4%
Price Change %	6.6%	3.9%	3.0%	5.8%	2.0%	1.2%	7.0%	5.4%	4.7%

(b). For 350 km/hr HSR lines

$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$			$(\frac{s_{it}}{D_i})^2$			$\sqrt{\frac{s_{it}}{D_i}}$		
Route Distance	500 km	850 km	1100 km	500 km	850 km	1100 km	500 km	850 km	1100 km
$\varepsilon_{q_A^*, s_H}$	-1.33	-0.78	-0.60	-1.73	-0.60	-0.36	-1.18	-0.90	-0.79
$\varepsilon_{p_A^*, s_H}$	-0.46	-0.27	-0.21	-0.57	-0.20	-0.12	-0.42	-0.32	-0.28
Traffic Change %	19.0%	11.2%	8.6%	34.6%	8.6%	5.1%	16.8%	12.9%	11.3%

$h(s_{it}, D_i)$	$\frac{s_{it}}{D_i}$			$(\frac{s_{it}}{D_i})^2$			$\sqrt{\frac{s_{it}}{D_i}}$		
Route Distance	500 km	850 km	1100 km	500 km	850 km	1100 km	500 km	850 km	1100 km
Price Change %	6.6%	3.9%	3.0%	8.1%	2.8%	1.7%	5.9%	4.6%	4.0%

To determine which form of $h(s_{it}, D_i)$ fits our data better, a Rivers-Vuong model selection test is conducted (Rivers and Vuong, 2002). This test is based on a lack-of-fit criterion (Bonnet and Dubois, 2010; Doi and Ohashi, 2018).

$$J_n^h(b^h) = \frac{1}{n}\sum(\hat{e}_{it}{}^h)^2 \tag{3.25}$$

where b^h is the set of parameters, n is the number of observations, and $\hat{e}_{it}{}^h$ are the residuals from the regressions ($\hat{\xi}_{it}{}^h$ for the airline traffic equation, and $\hat{v}_{it}{}^h$ for the airline price equation). The alternative model can have the parameters $b^{h'}$. Under the null-hypothesis that $J_n^h(b^h)$ and $J_n^{h'}(b^{h'})$ are the same, the test statistics T follows an asymptomatically normal distribution:

$$T = \frac{\sqrt{n}}{\hat{\sigma}_n^{hh'}}\{J_n^h(\hat{b}^h) - J_n^{h'}(\hat{b}^{h'})\} \tag{3.26}$$

where $\hat{b}^h$ is the estimate of b^h and $\hat{\sigma}_n^{hh'}$ is the estimator of the asymptotic variance of the difference between $J_n^h(\hat{b}^h)$ and $J_n^{h'}(\hat{b}^{h'})$. The selection procedure is to compare the sample value of T with critical values of standard normal distribution. We compare pair-wise the three competing forms of $h(s_{it}, D_i)$: $\frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ and $\sqrt{\frac{s_{it}}{D_i}}$. The results from the River-Vuong test are shown in Table 3.10. For both airline traffic and price equations, the model with $(\frac{s_{it}}{D_i})^2$ significantly outperforms the other two, by producing the smallest overall residuals $J_n^h(\hat{b}^h)$. This suggests that HSR speed effect can diminish fast with route distance, i.e., air-HSR substitutability.

Table 3.10 River-Vuong test for the assumed functional forms of $h(s_{it}, D_i) = \frac{s_{it}}{D_i}$, $(\frac{s_{it}}{D_i})^2$ or $\sqrt{\frac{s_{it}}{D_i}}$

(a). For airline traffic volume equation

Model h \ Model h'	$\frac{s_{it}}{D_i}$	$\sqrt{\frac{s_{it}}{D_i}}$
$(\frac{s_{it}}{D_i})^2$	-2.657***	-8.064***
$\frac{s_{it}}{D_i}$		-10.09***

(b). For airline price equation

Model h \ Model h'	$\frac{s_{it}}{D_i}$	$\sqrt{\frac{s_{it}}{D_i}}$
$(\frac{s_{it}}{D_i})^2$	-10.771***	-11.771***
$\frac{s_{it}}{D_i}$		-11.972***

Note: A more negative statistic suggests the superiority of one model to the other. The *** suggests that the Type I error to reject the null hypothesis that the two models are the same is less than 1%.

3.7 Concluding Remarks

This study investigates, both theoretically and empirically, the effects of HSR speed on airline traffic and price, taking into account the degree of the substitutability between airlines and HSR on different markets. To the best of our knowledge, this is the first study to explore how airline and HSR service substitutability can alter HSR speed effect on airline traffic and price. In addition, our model incorporates two countervailing effects of HSR speed on airlines, namely the travel-time effect and the safety effect: increasing HSR speed reduces HSR travel time but may bring about

safety concern, which is especially true in emerging HSR markets such as China. This is also the first study to incorporate the safety effect of HSR speed analytically.

The theoretical model suggests that HSR speed effect is stronger when airline and HSR services are more substitutable (i.e., on short-haul routes). The HSR speed effect depends on the relative dominance of travel-time and safety effect. HSR speed reduction increases airline traffic and price when travel-time effect dominates, while it reduces airline traffic and price when safety effect dominates. In addition, HSR speed has a larger impact on airline traffic volume than on airline price. Lastly, HSR speed effect can be moderated by inter-airlines competition, suggesting that more intense competition among the airlines in one market can reduce HSR speed effect on airlines.

The natural experiment of China's HSR speed reduction helps unbiasedly estimate HSR speed effect on airline traffic volume and price. The estimation indicates that HSR speed reduction increased both airline traffic and price, suggesting the dominance of the travel-time effect. More importantly, the empirical evidence confirms that HSR speed effect is stronger when airline and HSR services are more substitutable. This result is robust with alternative econometric specifications. By conducting model selection tests, it is found that the HSR speed effect on airlines declines with the route distance but increases with HSR speed in a square fashion. The HSR speed effect thus diminishes fast with air-HSR substitutability. We also tried to identify the 7.23 rear-ending short-term accident. The accident effect is, however, statistically insignificant with the use of quarterly data, as the accident effect attenuated probably very fast within a short period.

This chapter also opens avenue for future research. First, HSR price is fixed in China, so that the strategic behavior of HSR cannot be modeled. This analysis should be regarded as a partial equilibrium without fully accounting for competition behavior and cost structure of HSR. Future study is thus called for on those markets with HSR being free to decide price. The HSR speed effect on HSR operating cost and its full impact on air-HSR competition can then be identified. Second, we have not considered airline and HSR frequencies adjustment. Yang and Zhang (2012) and D'Alfonso et al (2015) model airline and HSR competing on frequencies. Airline and HSR frequencies could be important service quality. HSR speed change could also change airline and HSR schedules and frequencies. The frequency and schedule information of airline and HSR in

China is difficult to retrieve. Future effort is suggested to take into account frequency and schedule for HSR speed effect estimation.

Chapter 4. Modeling Airline Competition in Markets with Legacy Regulation: The case of the Chinese domestic markets

4.1 Introduction

Competition analysis is at the core of industrial organization economics (Dixit, 1979; Bresnahan, 1981, 1987; Singh and Vives, 1984). Economic analysis for the airline industry is no exception. Empirical studies have been conducted to identify the type of competition between airlines (i.e. Cournot, Bertrand or cartel). Brander and Zhang (1990; 1993) estimate conduct parameters for airlines providing homogenous services. They show that American Airlines and United Airlines competed close to a *Cournot* type in the duopoly markets out of Chicago O'Hare airport. Oum et al. (1993) also include oligopoly routes at the same airport and conclude that airlines' conducts differentiate with each other's and are affected by market share distribution and route distance.

Berry, Carnall, and Spiller (BCS 1996) adopt the Berry, Levinsohn and Pakes (BLP 1995) structural model to estimate a general type of airline competition with differentiated products in the US domestic market. Airlines are assumed to conduct Bertrand competition. Berry and Jia (2010) adopt the same model as BCS (1996) to study the evolution of air travel demand and airline cost structures in the US airline markets. This BLP type structural model with assumed Bertrand competition has been commonly used in other airline competition studies such as Lee's (2013) analysis of the Delta and Northwest Airlines merger and Yan and Winston's (2014) study on the welfare effect of possible airport privatization in the San Francisco Bay Area. Aguirregabiria and Ho (2012) extend the method and incorporate dynamic elements in airline competition analysis.

In fully deregulated aviation markets, such as those in the US, the assumption of Bertrand or Cournot competition may be justified, because airlines are able to compete freely on fares, flight frequencies and route entries (Dresner et al., 1996; Windle and Dresner, 1999). However, aviation markets in many countries are still subject to various legacy regulations. Although China became the world's second largest aviation market since 2005, its domestic market has been dominated by a few state-owned airlines with various regulations on airline competition, route entry, airport slot

allocation, and input procurements such as aircraft, fuel and pilots (Fu et al., 2015a, b). Unlike the fully deregulated US market, airlines in China are not always allowed to compete freely. Compared to state-owned airlines based in mega hubs such as Shanghai, Beijing and Guangzhou, private airlines based in other airports often face stricter regulations on route entry and airport slot acquisition. Although since 1997 Chinese airlines have been allowed to freely discount the 'standard' fares set by the government, airlines' attempts at aggressive pricing have been repeatedly warned and penalized by the Civil Aviation Administration of China (CAAC), the regulator and de facto owner of the largest state carriers. Zhang and Round (2011) find that in the absence of effective anti-trust laws in China, state-owned carriers are suspected to collude on price in selected markets. Airlines in China, therefore, may not compete freely in price (Bertrand) or quantity (Cournot). Applying a standard BLP method to markets with legacy regulation may yield biased estimation. Given that a large number of aviation markets in the world that have yet to be fully deregulated,[48] there is a need to explicitly incorporate possible constraints on airlines' competition decisions in empirical studies.

Nevo (2001) incorporates "perfect collusive pricing" into the BLP structural model, considering the hypothetical case in which a monopolist maximizes the joint profit of all products in the market. The price-cost margin predicted under such a perfect collusion model can be compared to the Nash-Bertrand outcome. The model that produces a better prediction (i.e., one that more closely matches the firm's real accounting data) is identified as the preferred method. Such an approach is known as the "menu" method in the literature. Hu et al. (2014) apply this method to study the Chinese passenger-vehicle industry, and find that the competition resembles more of a Bertrand competition than perfect price collusion.

However, the assumption of perfect price collusion in Nevo (2001) can be very restrictive to exclude all intermediate collusion types. Ciliberto and Williams (2014) thus model intermediate degrees of airline price collusion by constructing and incorporating an index of airline multi-market contacts into the BLP specification. A more flexible approach is proposed by Sudhir (2001), who develops a weighted profit model for the US auto-mobile market. A firm is assumed to internalize

[48] Whereas legacy regulations are present in most developing countries' domestic markets, even many international routes between developed economies, such as those between Hong Kong, Japan, Korea, and Australia, still face various capacity, route entry and flight frequency regulations. For discussions on the regulation and liberalization of international markets, see for example Fu et al. (2010), Adler et al. (2014).

part of its rivals' profits. Firms are identified as being more collusive when they put more weight on other firms' profits.

Building on previous studies, this chapter proposes an empirical approach to analyzing airline competition by accounting for possible regulation effects. With a general specification, a range of competition regimes (e.g., Bertrand, Cournot, or collusion) can be considered and empirically identified in the BLP framework. As regulations restrict airlines' ability to compete freely, we analyze market equilibrium using a competition model that resembles the weighted profit model (Sudlhir, 2001). We also adopt the "menu" approach (Nevo, 2001) to benchmark the performance of the proposed model against the models in which airlines are assumed to compete a la Cournot or Bertrand. Such a framework is applied to the Chinese domestic markets, for which better estimation and prediction results are obtained compared with BLP methods under standard Bertrand or Cournot competition. This study not only provides rich empirical results on the Chinese aviation industry in terms of passenger preference and airline competition, but also constitutes a new approach for modeling firm competition in the presence of possible regulatory constraints. It may also be extended for the analysis of markets with other types of constraints such as the limits of airport slots and air space, airport curfew, or international markets that are not fully liberalized.

The remainder of this chapter is organized as follows. Section 4.2 briefly reviews the background and current status of the Chinese airline industry. Section 4.3 establishes the econometric model and explains the algorithms used in the estimation. Section 4.4 describes the data sources, variable definitions, and selection of Instrument Variables (IVs) for the generalized method of moments (GMM) estimation. Estimation results and interpretations are given in Section 4.5. Section 4.6 summarizes and concludes the study.

4.2 Background on the Chinese Airline Market

The Chinese aviation industry has experienced rapid growth, achieving an average annual growth over 10% between 1990 and 2015 in terms of number of passengers (CAAC 2015). In 2005, China became the world's second largest aviation market in terms of scheduled capacity. Despite such phenomenal growth and some deregulation policies, much commercial regulation remains in the

Chinese domestic markets. Airfare and route entry had been strictly regulated until 1997, when airlines were allowed to provide discounts off the standard fares set by the government, which effectively relaxed price control. This has been the most influential deregulation to promote airline competition and has led to widespread price competition and substantial price reduction (Zhang and Round, 2011; Fu et al., 2015b). However, continuous price wars in the following years led to serious financial losses among airlines owned by state and local governments. As a response, CAAC coordinated consolidations of the nine largest state-owned carriers into three big airline groups in 2002, namely the so called "big three" including Air China, China Eastern and China Southern. The claimed policy objective is to reduce excessive competition and help carriers achieve economies of scale. The formed big-three airline groups are balanced in terms of network geographic coverage, capitalization and market shares, so that none of them owns a significant market power over the other two (Zhang and Round, 2009; Zhang and Zhang, 2017).

As another measure to stabilize the domestic market and limit fierce competition among state-owned carriers, route entry has remained regulated for a long time, especially for services to the large hub airports. This restriction has been partially relaxed since 2006. Prior approval is no longer required for most airports, whereas regulations have been retained for routes out of the eight busiest airports (Fu et al., 2015a). Since 2010, only routes involving the four mega-hubs have needed formal approval (i.e. Beijing Capital, Shanghai Hongqiao, Shanghai Pudong, and Guangzhou Baiyun). On the input acquisition side, airline's fleet expansion plans need prior approval from CAAC to ensure "orderly" industry growth. Among others, airlines need to achieve certain utilization thresholds such as load factor and daily aircraft operation hours. Although such measures do increase the industry capital utilization rates, they also restrict the overall supply of industry capacity and thus prevent large scale price wars.

With the CAAC's 2005 approval of private sector participation in the civil aviation industry, a few private airlines have been formed including Okay Airways, United Eagle Airlines and Spring Airlines. Spring Airlines positions itself as a low-cost carrier (LCC) and achieved sustained growth in scale and profit with an annualized average growth rate of more than 10%. Still, private airlines play a minor role in the sector with a combined market share of less than 10% (Wang et al., 2017). Fu et al. (2015b) find that private airlines face stricter restrictions to entering and expanding capacity on major routes. Despite being one of the most successful LCCs in China and in the region,

Spring Airlines has never exceeded a 20% market share in the most travelled routes such that it has not imposed significant competitive pressure on the full-service carriers as overseas LCCs. That said, Fu et al. (2015a, b) note an increasing deregulation trend in China since year 2006. Regulations on pricing, capacity and route entry have been largely removed on routes other than those linked to major hub airports. Private and low-cost carriers are granted more freedom to compete against the state-owned carriers in secondary domestic routes and selected international markets. With their generally higher efficiency and lower cost, for example, private and low-cost airlines have initiated services on thin routes to small to medium airports, where they claimed large market shares or even monopoly.

To summarize, although the Chinese aviation market has become much more liberalized than it was decades ago, substantial regulations are still present in areas such as route entry, slot allocation and fleet acquisition. These regulations are likely to limit airlines' ability to compete freely as carriers do in fully deregulated markets in North America and Europe. These constraints are not universally imposed in the whole domestic markets, with secondary routes being much more liberalized compared to routes linked to hub airports. Therefore, simply assuming Chinese airlines engage in a particular type of competition is likely to yield biased estimation results. There is a need to develop an econometric approach that allows for alternative types of competition, and the flexibility for one airline's strategy and behavior to differ across the routes on which it competes.

4.3 Model and Estimation Method

This section first specifies passenger preference and demand modeling. It then discusses alternative modeling methods on airline competition and the corresponding market equilibria that followed these alternative competition specifications.

4.3.1. Travel demand side and passenger utility

The specification of air travel demand is in the spirit of BCS (2006), Berry and Jia (2010), Ciliberto and Williams (2014). The utility of consumer *i* when consuming product *j* in market *t* is given by Eq. (4.1):

$$u_{ijt}=\boldsymbol{x_{jt}\beta}-\alpha\, p_{jt}+\xi_{jt}+v_{it}(\lambda)+\lambda\epsilon_{ijt} \tag{4.1}$$

where

- x_{jt} is a vector of observable product characteristics including route distance, airline brand and tourism destination, etc.;
- β is a vector of coefficients of product characteristics;
- α is the marginal disutility of a price increase for the passenger;
- ξ_{jt} is the product characteristics unobservable to the researchers;
- λ is the nested logit parameter which is between 0 and 1, and $v_{it}(\lambda)$ is the nested logit error. [49]

As in Berry and Jia (2010), a nested logit model is adopted under the assumption that the error term in Eq. (4.1) follows a Generalized Extreme Value (GEV) distribution. A closed-form demand (market share) function can be derived as follows: [50]

$$v_{it}(\lambda)+\lambda\,\epsilon_{ijt} \tag{4.2}$$

Specifically, conditional on choosing air travel, the proportion of consumers who purchase product *j* in market *t* is given:

$$\frac{e^{\left(\boldsymbol{x_{jt}\beta}-\alpha p_{jt}+\xi_{jt}\right)/\lambda}}{D_t} \tag{4.3}$$

where the denominator D_t is defined by:

[49] There are two nests considered, which include the outside good of no air travel and all the airline products.

[50] Berry (1994) shows the derivation of this nested logit specification from a purely random coefficient discrete choice model using the mean utility approach.

$$D_t = \sum_j e^{\left(\boldsymbol{x_{jt}\beta} - \alpha p_{jt} + \xi_{jt}\right)/\lambda} \tag{4.4}$$

The proportion of consumers who choose air travel is:

$$s_t\left(x_t, p_t, \xi_t, \theta_d\right) = \frac{D_t^{\lambda}}{1 + D_t^{\lambda}} \tag{4.5}$$

The overall market share of product *j* in market *t* is as defined by:

$$s_{jt}\left(x_t, p_t, \xi_t, \theta_d\right) = \frac{e^{\frac{\boldsymbol{x_{jt}\beta} - \alpha p_{jt} + \xi_{jt}}{\lambda}}}{D_t} \times \frac{D_t^{\lambda}}{1 + D_t^{\lambda}} \tag{4.6}$$

The demand parameters θ_d include the taste for product characteristics β, the disutility of price α, and the nested logit parameter λ. The unobservable characteristics ξ_{jt} can be expressed as below by inverting the demand function.

$$\xi_{jt} = s^{-1}\left(x_t, p_t, s_t, \theta_d\right) \tag{4.7}$$

With the contraction mapping method proposed by BLP (1995), through numerical iterations, we can calculate the value of ξ_{jt} with Eq. (4.8) [51]:

$$\xi_{jt}^{M} = \xi_{jt}^{M-1} + \lambda\left[\ln s_{jt} - \ln s_{jt}\left(x_t, p_t, \xi_t, \theta_d\right)\right] \tag{4.8}$$

With the value of ξ_{jt}, GMM method can be utilized based on the moment conditions between the demand IVs and the unobservable ξ_{jt}, as Eq. (4.9) suggests. The next section describes the selection of IVs.

$$\mathrm{E}\left(h(z_t)\xi\left(x_t, p_t, s_t, \theta_d\right)\right) = 0 \tag{4.9}$$

[51] The initial ξ_{jt}^{0} is set to be a zero vector with the dimension of number of markets. The iteration stops when difference between the two iterated ξ values small then pre-set threshold.

Using the nested logit demand function, a reduced-form IV regression can be derived to estimate demand parameters (see Appendix C1), [52] which provides a robustness check for the sophisticated BLP method. If the numerically simulated GMM weight matrix of BLP works well, the demand estimations from the two methods should be close to each other as both estimators are consistent asymptotically.

4.3.2 Modeling of airline competition

4.3.2.1 Bertrand equilibrium

Bertrand competition assumes that each airline competes in price to maximize the total profit of its products. Suppose that there are a total of F airlines on route t, each of which produces J_{ft} different products where $f \in \{1,\ldots,F\}$. It is also assumed that airlines have constant marginal costs, thus the profit for airline f at market t is:

$$\Pi_{ft} = \sum_{j=1}^{J_{ft}} \left(p_{jt} - mc_{jt}\right) M_t s_{jt}\left(p_t, x_t, \xi_t; \theta_d\right) - FC_{ft} \tag{4.10}$$

where $s_{jt}\left(p_t, x_t, \xi_t; \theta_d\right)$ is the market share of product j at market t, a function of all other airline products on that route; M_t is the market size, and FC_{ft} is the fixed cost which does not enter the first order condition. Li and Huh (2011) prove the existence of a pure-strategy Nash-Bertrand equilibrium for the nested logit model. At equilibrium the price p_{jt} of product j by firm f at market t must satisfy the first-order condition:

$$s_{jt}\left(p_t, x_t, \xi_t; \theta_d\right) + \sum_{r \in J_{ft}} \left(p_{rt} - mc_{rt}\right) \frac{\partial s_{rt}(p_t, x_t, \xi_t; \theta_d)}{\partial p_{jt}} = 0 \tag{4.11}$$

[52] For details about this reduced regression, see for example Berry (1994), and Yan and Winston (2014)..

This set of equations implies the price-cost margins for each product. The markups can be solved for explicitly by defining V_{jrt}=-$\partial s_{rt}/\partial p_{jt}$, where $j, r = 1, \ldots, J_t$ and $J_t = \sum_{f=1}^{F} J_{ft}$ is the total products of air travel in market t:

$$\Omega_{jrt}=\begin{cases} V_{jrt}, & if\{r,j\}\subset\{1,\ldots,J_{ft}\} \\ 0, & \text{otherwise} \end{cases} \tag{4.12}$$

The derivations of V_{jrt} is reported in Appendix C2. Denote Ω_t to be a $J_t \times J_t$ matrix. In vector notation the first-order conditions become:

$$s_t(p_t)-\Omega_t(p_t-mc_t)=0 \tag{4.13}$$

where $s_t(\cdot)$, p_t, and mc_t are $J_t \times 1$ vectors of mark shares, prices, and marginal cost, respectively. This implies a markup Eq. (4.14):

$$(p_t-mc_t)= \Omega_t^{-1} s_t(p_t) \tag{4.14}$$

We assume a linear form of marginal cost as follows:

$$mc_t=w_t\psi+\omega_t \tag{4.15}$$

where

- w_t is a vector of observed cost characteristics;
- ψ is a vector of cost parameter;
- ω_t is an unobserved cost shock.

and thus, one has:

$$\omega_t=p_t-\Omega_t^{-1} s_t(p_t)-w_t\psi \tag{4.16}$$

With the estimated value of ω_t, we can use exogenous variables z_t that are mean independent with ω_t to construct the moment conditions as:

$$\mathrm{E}\left(g(z_t)\omega_t\left(x_t,p_t,s_t;\theta_{d,}\psi\right)\right)=0 \tag{4.17}$$

These additional moment conditions of Eq. (4.17) from the supply side can be added to those from the demand side (see Eq. (4.9)) for a joint estimation of parameters θ_d, ψ. The demand parameters θ_d also enter the supply side moment conditions to improve the estimation efficiency of θ_d.

4.3.2.2 Cournot equilibrium

The Cournot equilibrium conditions for the BLP model are also derived in this section. Despite empirical evidence that airlines do compete in Cournot in selected markets (see for example Brander and Zhang 1990), to our best knowledge Cournot equilibrium has not been developed and applied in structure BLP models in the literature. This is the first BLP study to model Cournot competition with product differentiation in oligopoly markets. To obtain the first order condition for the Cournot equilibrium, we first derive the inverse demand function as Eq. (4.18), expressing airline ticket prices as a function of the market shares of all products and the outside goods $s_0=\frac{1}{1+D_t^{\lambda}}$ (derivation details in Appendix C3).

$$p_{jt}=\frac{1}{\alpha}\left[\boldsymbol{x_{jt}\beta}+\xi_{jt}+(\lambda\text{-}1)\ln(\frac{s_t}{s_0})\text{-}\lambda\ \ln(s_{jt})+\lambda\ \ln(s_0)\right] \tag{4.18}$$

Cournot competition assumes that airlines compete in quantity (market share in our case, as market size M_t is constant for each market) to maximize the total profit of its products portfolio. It is assumed again that there are F airlines on route t and each of them has a constant marginal cost. The profit of airline f is:

$$\Pi_{ft}=\sum_{j=1}^{J_{ft}}\left(p_{jt}\left(s_t,x_t,\xi_t;\theta_d\right)\text{-}mc_{jt}\right)M_t s_{jt}\text{ -}FC_{ft} \tag{4.19}$$

This set of equations imply price-cost margins for each air travel product. The markups can be solved for explicitly by defining R_{jrt}=-$\partial p_{rt}/\partial s_{jt}$, $j, r = 1, \ldots, J_t$:

$$\Gamma_{jrt}=\begin{cases} R_{jrt}, & if\ \{r,j\}\subset\{1,\ldots,J_{ft}\} \\ 0, & \text{otherwise} \end{cases} \tag{4.20}$$

The derivations of R_{jrt} is shown in Appendix C3. Γ_t is a $J_t \times J_t$ matrix and in vector notation the first-order conditions become:

$$\left(p_t(s_t)\text{-}mc_t\right)+\Gamma_t s_t=0 \tag{4.21}$$

where $p_t(\cdot)$ and mc_t are $J_t \times 1$ vectors of prices, and marginal cost, respectively.

This implies a markup equation:

$$p_t\text{-}mc_t=\text{-}\Gamma_t s_t \tag{4.22}$$

and so

$$\omega_t=p_t\text{-}w_t\psi+\Gamma_t s_t \tag{4.23}$$

As in the Bertrand equilibrium, with estimated value of ω_t from Eq. (4.23), the exogenous variables z_t that are mean independent with ω_t are used to construct the moment conditions:

$$\mathrm{E}\left(g(z_t)\omega_t\left(x_t,p_t,s_t;\theta_{d,}\psi\right)\right)=0 \tag{4.24}$$

4.3.2.3 Weighted profit equilibrium

As discussed in Section 4.2, legacy regulations on route entry, fleet expansion and airport slot acquisition are present in China. Although many such regulations are not meant to directly

intervene in airlines' pricing strategies, they are expected to prevent airlines from competing with each other freely. To model such market conditions, it is considered that Chinese airlines maximize their profits subject to the constraint that their rivals' profits are also above a threshold. This is likely to be the case especially for the most travelled routes where CAAC is keen to maintain the profitability of major state-owned airlines, an "orderly" market outcome desired by the regulator. If an airline competes aggressively and disturbs the so-called "market order", it may be penalized with its slots at hub airports confiscated, or forbidden to serve other lucrative routes in the future (Zhang and Round, 2011). Since these regulations are mainly imposed on densely travelled routes, the effects on competition should be most prominent in these markets. On the other hand, in the absence of effective anti-trust laws airlines in China may form self-enforcing cartels without regulator's intervention. Major Chinese airlines, especially the "Big Three" (i.e. Air China, China Southern, China Eastern), are balanced in market power and thus are likely to sustain a cartel. If this is the case, such a cartel can be nation-wide covering both dense and thin markets. The cartel is likely to be more stable in the more concentrated routes with fewer number of airlines. [53]

As in the cases of Bertrand and Cournot equilibria, consider F airlines competing on the route, each produces J_{ft} different travel products and has a constant marginal cost. Firm f's rivals are denoted as $f^{-} \in \{1,\ldots,F\}/f$. Airline f decides its ticket prices to maximize its profit, with a constraint that its rivals' profits cannot be less than a minimum level $\underline{\Pi}_{f^{-}t}$:

$$\begin{aligned} \underset{p_{jt}}{\text{Max}} \quad \Pi_{ft} &= \sum_{j=1}^{J_{ft}} \left(p_{jt}-mc_{jt}\right) M_t s_{jt}\left(p_t,x_t,\xi_t;\theta_d\right) - FC_{ft} \\ \text{s.t.} \quad & Q_{f^{-}t}\left(p_t-mc_t\right)-FC_{f^{-}t} \geqslant \underline{\Pi}_{f^{-}t} \end{aligned} \tag{4.25}$$

where $Q_{f^{-}t}$ is a $(F\text{-}1)\times J_t$ matrix, $p_t - mc_t$ is a $J_t \times 1$ vector, and $F_{f^{-}t}$ and $\underline{\Pi}_{f^{-}t}$ are $(F-1)\times 1$ vectors. Each row vector of $Q_{f^{-}t}$ represents rivals' products:

[53] We expect more concentrated industries to benefit from cartel formations for two reasons. First, in a static setting, as the number of firms rises, we expect the free-rider problem to worsen (Rodrik, 1986). Second, in a super-game setting, we expect that the ability to maintain a cooperative outcome deteriorates as the number of firms increases (Friedman, 1971).

$$Q_{fj}=\begin{cases} q_j & \text{if product } j \text{ belongs to firm } f \\ 0 & \text{otherwise} \end{cases} \tag{4.26}$$

Transforming the above constrained profit maximization problem into a Lagrange function with the Lagrange multipliers $\Phi=[\phi_1,\ldots,\phi_{F-1}]'$ gives:

$$\begin{aligned} \underset{p_{jt},\Phi}{Max}\ \Pi_{ft} &= \sum_{j=1}^{J_{ft}} \left(p_{jt}-mc_{jt}\right) M_t s_{jt}\left(p_t,x_t,\xi_t;\theta_d\right) - FC_{ft} + \left\{ Q_{f^-t}\left(p_t-mc_t\right) - F_{f^-t}\underline{\Pi}_{f^-t}\right\}' \Phi \\ &= \sum_{j=1}^{J_{ft}} \left(p_{jt}-mc_{jt}\right) M_t s_{jt}\left(p_t,x_t,\xi_t;\theta_d\right) - FC_{ft} \\ &+ \sum_{g\neq f} \left\{ \phi_g \left[\sum_{i=1}^{J_{gt}} \left(p_{it}-mc_{it}\right) M_t s_{it}\left(p_t,x_t,\xi_t;\theta_d\right) - FC_{gt} \right] \right\} \end{aligned} \tag{4.27}$$

Solving the above Lagrange function is equivalent to maximizing an airline's own profit plus others' profit, weighted by the Lagrangian multiplier vector ϕ. This leads to the weighted profit model as in Sudhir (2001). The larger the value of the Lagrangian multipliers, the more restrictive constraints are (i.e., stricter regulations or stronger price collusion).

The first order condition with respect to p_{jt} is as in Eq. (4.28):

$$\frac{\partial \Pi_{ft}}{\partial p_{jt}} = M_t \left\{ s_{jt} + \sum_{j=1}^{J_{ft}} \left(p_{jt}-mc_{jt}\right) \frac{\partial s_{jt}}{\partial p_{jt}} + \sum_{g\neq f} \phi_g \left[\sum_{i=1}^{J_{gt}} \left(p_{it}-mc_{it}\right) \frac{\partial s_{it}}{\partial p_{jt}} \right] \right\} = 0 \tag{4.28}$$

In theory, the value of ϕ can be airline-pair and route specific. However, allowing such specificity can create an extreme burden on model identification.[54] To make the empirical estimation feasible

[54] For example, F airlines to compete on one route, which will lead to a total $F(F-1)$ values of ϕ_g to estimate for each market. With more than 1,000 routes, the vector ϕ will be of dimension $1000F(F-1)$. Even we only distinguish ϕ_g by the airline, not the market, suppose we have more than 8 airlines (which will be shown in the later

while still allowing useful implications to be drawn, we simplify by letting ϕ to be dependent on route traffic level. We classify markets into four categories based on their ranks of traffic volumes, and assign different values of ϕ to each category. Specifically, markets are grouped into four categories per their traffic volumes: (i) the top 25%. (ii) top 25%-50%. (iii) top 50%-75%. (iv). others.

If policy interventions in the dense markets are effective, one would expect the values of ϕ to be more significantly positive. If airlines maintain a tacit or even explicit collusion without government intervention, the values of ϕ can be significantly positive for all the route categories, especially on concentrated routes.

Define $V_{jrt}=-\partial s_{rt}/\partial p_{jt}$, $j,r=1,\ldots,J_t$, and

$$H_{jrt}=\begin{cases} V_{jrt}, & if\ \{r=j\}\subset\{1,\ldots,J_{ft}\} \\ \phi_m V_{jrt}, & \text{Otherwise} \end{cases} \tag{4.29}$$

where ϕ_m, m=1,2,3,4 represents the weight of the route categories for the top 25%, top 25%-50%, top 50%-75% and other markets respectively. H_t is a $J_t \times J_t$ matrix. In vector notation the first-order conditions become:

$$s_t(p_t)-H_t(p_t-mc_t)=0 \tag{4.30}$$

where $s_t(\cdot)$, p_t, and mc_t are $J_t \times 1$ vectors of market shares, prices, and marginal cost, respectively. This implies the following markup equation:

$$p_t-mc_t=H_t^{-1}s_t(p_t) \tag{4.31}$$

then, we have

$$\omega_t=p_t-H_t^{-1}s_t(p_t)-w_t\psi \tag{4.32}$$

data description section), as almost any two of them have direct contact in some markets. We will have as many as $8 \times 7 = 56$ values of ϕ_g to estimate.

With the estimated value of ω_t from Eq. (4.32), we can use the exogenous variables z_t (same as in the Bertrand and Cournot models) that are mean independent with ω_t to construct the moment conditions as:

$$\mathrm{E}\left(g(z_t)\omega_t\left(x_t, p_t, s_t; \theta_d, \psi\right)\right) = 0 \tag{4.33}$$

4.4 Variables, Data, and Instrument Variables (IVs) Selection

Analogous to Berry and Jia (2010), in the demand function the following characteristics are included in the vector $\boldsymbol{x_{jt}}$ in addition to airfare *Fare*: route flying distance *Distance* (for connecting flights, it is defined as the sum of every segment's distance); distance squared *Distance_squared*; number of connections *Connection*; flight frequency *No. of Departure*; the average number of destinations the airline serves out of the two endpoint airports *No. of Destination*; the tour route dummy *Tour* [55] ; the airport congestion as reflected by its slot controlled status *Slot_control* ; and the income level of the endpoint cities on the route *Income* [56].

In the marginal cost function specified for different competition regimes, we consider the following variables in vector $\boldsymbol{w_t}$: flying distance *Distance*; the number of connection *Connection*; a hub variable defined as the airline's market shares in the endpoint airports *Hub*; and the slot control variable *Slot_control*. Airlines' marginal costs can significantly differ between short-to-medium haul routes and long-haul routes due to different aircraft sizes, on-board services and crew costs. Therefore, similar to Berry and Jia (2010) and Lee (2015), we also allow two sets of cost parameters: one for routes shorter than 2,400 km, and the other for routes longer than 2,400 km.

[55] The tour dummy is defined for popular tourist destinations in China. A similar definition was used by Zhang and Round (2009), Fu et al, (2015).

[56] The impact of the income on air travel utility is two-fold. First, people with higher income should attach higher utility on the air travel. Second, since the air travel is a derived demand, the air travel derived from the economic activity of more prosperous markets implies higher utility to passengers.

Airline-route specific data are compiled from the PaxIS database of the International Air Transport Association (IATA). The PaxIS database is a GDS (Global Distribution System) that records airlines' ticket booking information. Monthly directional itinerary data are retrieved which contains ticket price and passenger number for each reporting Chinese airline in each origin-destination (OD) market. The airfare data in PaxIS is an aggregate average for all different fare classes and all flights operated by each airline. [57] PaxIS nevertheless distinguishes direct and connecting flights as distinct products.

A market is defined as a city-pair, whereas a product is defined as a unique combination of directional airport-pair, airline, and direct/connecting flight. [58] Direct and connecting flights provided by the same airline are treated as different products. Two connecting flights transferred via different third airports are also regarded as different products.

The Official Airline Guide (OAG) data are supplemented for airline route-specific flight frequency. The OAG reports airlines' scheduled flight frequency for each direct OD segment. The flight frequency variable is constructed for connecting flights reported in PaxIS. Without detailed airline flight schedules within the 24-hour cycle, it is impossible to match connection flights individually. We thus use the minimum flight frequency among all segments of the connecting flight frequency, a similar approach as those used in Adler and Smilowitz (2007) and Adler et al. (2014). Route distance and airlines' airport presence (market share in the airport, and the number of routes originating from the airport) are also obtained from the OAG data.

Other socioeconomic data are compiled from various databases and sources. The city level population and personal income (GDP per capita) data are available from the city statistical yearbooks published by city census bureaus. Cities' monthly rainfall and temperature data are also acquired from the National Meteorological Centre of China, which are used as additional cost

[57] In addition, ticket price reported by PaxIS does not count tax, airport charges and fuel surcharge.

[58] For the cities with more than one airport, flights to different airports are treated as different products. There are only two cities that have more than one airport: Hongqiao (SHA) and Pudong (PVG) airports in Shanghai; and Beijing Capital (PEK) and Nanyuan (NAY) airports in Beijing.

instruments to improve estimation efficiency. Airport slot control status is collected from Fu and Oum (2015) [59].

It is suspected that, in some very thin markets, passenger preference and airline competition behaviors could be very different. We thus filter out very small regional markets to only consider the routes linking cities with more than four million population, which are the top 100 populous cities in China. Such a dataset covers more than 90% of the passenger travels in the domestic markets. Airlines included in this study are Air China (CA), China Eastern (MU), China Southern (CZ), Hainan (HU), Shanghai (FM), Shenzhen (ZH), Xiamen (MF), with other small-sized airlines grouped into one category as "Other". [60]

We acquired data for the five-month period during August to December in 2010. The moment conditions for the GMM estimation are not affected by serial dependence of error terms ξ_t and ω_t, because the same route at different months can be regarded as different markets. Because data are collected for a relatively short period, passenger demand and airline competition pattern do not change significantly over the five months. [61] Per the above sample selection criteria, we end up with a total of 5,944 markets and 18,349 airline products in the sample.

Instrument variables (IVs) must be specified for both the demand and pricing moment conditions. Any factor that is correlated to the observed variables but uncorrelated with demand or supply disturbances ξ_t and ω_t can be appropriate IVs. Following previous studies (BCS, 2006; Berry and Jia, 2010; Yan and Winston; 2014; Lee, 2015; Luo, 2015), the following instruments are used for the demand moments with strong exogeneity assumption $\mathrm{E}(\xi_t | z_t) = 0$.

- The number of products in each market;

[59] Slot controlled Chinese airports include Beijing (PEK), Shanghai Pudong (PVG), Guangzhou (CAN), Xi'an (XIY), Shanghai Hongqiao (SHA), Chongqing (CKG), Shenzhen (SZX), Chengdu (CTU), Wuhan (WUH), Hangzhou (HGH), Nanjing (NKG), Qingdao (TAO), Xiamen (XMN), Dalian (DLC), Changsha (CSX), Haikou (HAK), Urmuqi (URC), Tianjin (TSN), Fuzhou (FOC) and Sanya (SYX).

[60] Spring Air, the largest private airline in China, is not included in the PaxIS dataset, as it uses its own ticket reservation system and is not obliged to report ticket itinerary information to the IATA.

[61] We tried to run our estimation using each month data separately. The estimation results are generally consistent, albeit with reduced estimation efficiency .

- The percentage of rivalry products that offer direct flights in the market;
- The number of rivalry products available in the market;
- The number of carriers in the market;
- The Hub status of each airline in the market;
- The 25th % percentile and 75th % percentile of fitted fares in a market. [62]
- The market size measured by the geometric means of the endpoint cities' population.

The characteristics of the rival airlines in the same market are included as IVs because they are excluded in the passenger utility function derived from consuming one particular product (u_{ijt} is the utility to consume product j , which does not directly depend on the product characteristics of the other products, x_{rt}). These variables are nevertheless correlated with the price of the consumed product via the markups in the first-order conditions of airline competition (Berry, 1994). These IVs are not as the traditional ones from the cost side, which shifting the price due to higher operating cost, while not directly affecting demand. That is, with imperfect firm competition, demand-side instruments can be variables that affect markups as well as variables that affect marginal cost (Berry, Levinsohn and Pakes, 1995). For example, the IV, the percentage of rivalry products that offer direct flights in the market is to affect the markup as it indicates the airline competition intensity, while this variable may also indicate the level of marginal cost as direct flight is more expensive to operate. Thus, no matter affecting operating cost or market up due to imperfect competition, these IVs should be valid.

The strong exogeneity condition $\mathrm{E}(\xi_t|z_t)$=0 implies the mean independence $\mathrm{E}(g(z_t)\xi_t)$=0 for the functional forms of the chosen IVs. To create the vector of IVs used for the estimation, we basically adopt the same set of IVs as Berry and Jia (2010), with additional functional forms of the IVs, and also select the ones that have the small empirical correlation with the simulated disturbance ξ_t. Airline flight frequency may be subject to endogeneity concern since it can also be correlated with the unobservable product characteristics ξ_t, and it is also because flight frequency is also affected by increasing air travel utility and demand (airlines increase flight frequency to accommodate

[62] Quantile regression on the ticket price is conducted to generate the predicted values of 25% and 75% quantiles of the ticket price in the market.

higher air travel demand), i.e., a simultaneous relationship (Berry and Jia, 2010; Fu et al, 2014). To address the endogeneity of the flight frequency, we first regress the flight frequency on characteristics of the end cities, and then replace the frequency variable with the fitted values (Fu et al., 2014). For the marginal cost shifter ω_t, our IVs include some of the demand instruments as well as additional exogenous cost shifter IVs such as monthly average rainfall and temperature in cities. The summary statistics is shown in Table 4.1.

Table 4.1 Summary Statistics of Major Variables

Variable	Mean	Std. Dev.	Min	Max	Unit
Product share	0.00033	0.00051	4.20E-08	0.0072428	Unit
Fare	132.07	46.37	24	761	USD
Distance	1,314.89	603.66	159	3922	Kilometer
Connection	0.17	0.24	0	1	Unit
No. Departure	90.45	92.83	30	630	Weekly
No. Destination	17.83	18.22	1	86	Unit
Tour	0.04	0.19	0	1	Dummy
Slot_control	0.83	0.37	0	1	Dummy
Income	51.04	14.35	15.49	91.09	RMB 1,000
Hub	0.21	0.18	0	1	Unit
Hub_connect	0.14	0.23	0	1	Unit
Market Population	9,995,725	3,560,943	4,190,057	25,800,000	Person
No. of Carrier	3.53	1.56	1	8	Unit
No. of Product	4.70	3.33	1	33	Unit

Variable	Mean	Std. Dev.	Min	Max	Unit
Temperature	12.47	9.46	-20.74	26.04	Centigrade
Rainfall	77.88	64.61	1.51	342.34	mm

4.5 Model Estimation Results

We first report the demand estimates based on the demand moment conditions only, then present the joint demand and airline cost estimates using both the demand and airline competition moment conditions. The joint estimates with different airline competition conducts, namely Bertrand, Cournot and weighted profit, are benchmarked for inferences and comparisons.

4.5.1 Demand estimation based on the demand moment conditions only

The demand estimates using both BLP and reduced-form regression are collated in Table 4.2. For reduced-form regressions, we adopt an ordinary least squares (OLS) approach and an IV approach to instrument the endogenous price variable. Our BLP and IV models produce very similar results, indicating the validity of the BLP method and the necessity to control for the price endogeneity. The OLS produces a positive price coefficient estimate, showing a strong price endogeneity due to the positive correlation between the unobservable characteristics ξ_t and the airfare. [63]

Our BLP and IV logit demand estimates are overall sensible with expected signs. Table 4.3 shows the median market price elasticity and the traveler's willingness to pay for the different product characteristics. These values can be directly compared to the US market estimates of Berry and Jia (2010), and Yan and Winston (2014).

[63] This can happen when the unobservable product characteristics, ξ_t, contains some unobservable quality factors associated to a higher airfare.

Table 4.2 Demand Function Estimation and Robust Test with IV and OLS Demand Estimation

Demand Variables	BLP	IV Logit	OLS Logit
Fare	-0.8501***	-0.7555***	0.0559**
	(0.0808)	(0.0591)	(0.0222)
Connection	-1.2957***	-1.4284***	-1.3315***
	(0.0187)	(0.0114)	(0.0104)
Constant	-11.0717***	-9.1751***	-9.541***
	(0.1141)	(0.0573)	(0.0526)
No. Destination	0.1223***	0.2921***	0.2846***
	(0.0494)	(0.0467)	(0.0433)
No. Departure	0.0281***	0.0267***	0.0387***
	(0.0014)	(0.0016)	(0.0014)
Distance	1.7262***	0.8753***	0.1326***
	(0.1192)	(0.072)	(0.0512)
Distance_squared	-0.4147***	-0.1444***	-0.0613***
	(0.0332)	(0.0169)	(0.0149)
Tour	0.9873	0.4355***	0.4616***
	(0.0521)	(0.0396)	(0.0368)
Slot_control	-0.5276***	-0.1706***	-0.0371*
	(0.0370)	(0.0231)	(0.0214)
Income	0.0579***	0.0222***	0.0245***

Demand Variables	BLP	IV Logit	OLS Logit
	(0.0020)	(0.0006)	(0.0005)
γ	0.6431	0.748***	0.6215***
	(0.0102)	(0.0525)	(0.0040)
Carrier Dummy			
OT	0.0065		
	(0.0782)		
CA	0.2981***	0.2103***	-0.2143***
	(0.0817)	(0.0492)	(0.0452)
MU	0.3609***	0.2095***	0.0488
	(0.0759)	(0.0410)	(0.0381)
CZ	0.4719***	0.3323***	0.0729*
	(0.0770)	(0.0405)	(0.0374)
HU	0.3082***	0.3443***	0.3362***
	(0.0813)	(0.0487)	(0.0454)
FM	0.2691***	0.2033***	0.0352
	(0.0830)	(0.0517)	(0.0479)
ZH	0.1876***	0.3089***	0.1386***
	(0.0832)	(0.0479)	(0.0444)
MF	0.3556***	0.0951*	-0.0425
	(0.1310)	(0.0494)	(0.0457)
No. of Obs	18,349	18,349	18,349

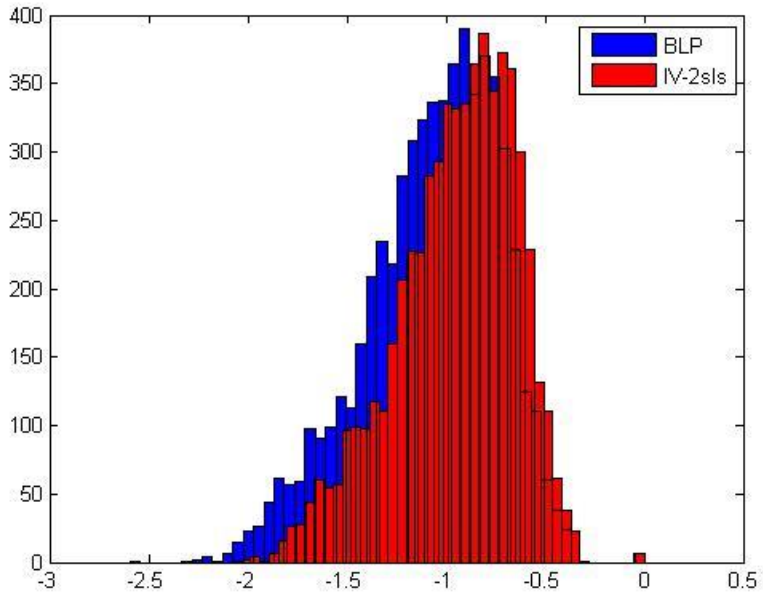
Note: * Significant at the 10% level; **Significant at the 5% level; *** Significant at the 1% level.

Table 4.3 Median price elasticity and willingness to pay for product attributes

	BLP	IV Logit	Berry and Jia (2010)	Yan and Winston (2014)	Brons et al. (2002)
Median price elasticity	-1.022	-0.9083	-1.55	-1.54	-1.146
Willingness to pay (US$)					
Additional weekly flight frequency	3.31	3.53	6.75	2.28	
Additional one destination valuation	0.14	0.38	1.17	0.20	
Airport without slot control	62.1	22.6	77.4	24.0	
Direct flight with no connection	152.4	189.1	224	212	

Our estimated price elasticity is -1.02 (BLP model) and -0.91 (IV regression model). The distribution of the route price elasticities is shown in Figure 4.1. These elasticity results on Chinese airline markets are similar to those of the developed countries (Berry and Jia, 2010; Yan and Winston, 2014). Zhang et al. (2013) use reduced-regression approach and find similar price elasticity of about -0.9 on the major Chinese routes out of Beijing, Shanghai, and Guangzhou. A meta-analysis in Brons et al. (2002) and a survey of Oum et al. (1992) show that air travel price elasticity is in the range of -0.8 to -2.0 for the liberalized markets of the developed countries. Despite the much lower average personal income in China, the air travel price elasticity is actually very close to the markets in developed economies. Such low price elasticity is in line with the findings of Chinese air travelers survey. Air travelers in China have much higher personal income than the average population, with half of them traveling for business purpose, and more than 40% of passengers having their airfares paid for by a third party (CAMIC, 2010).

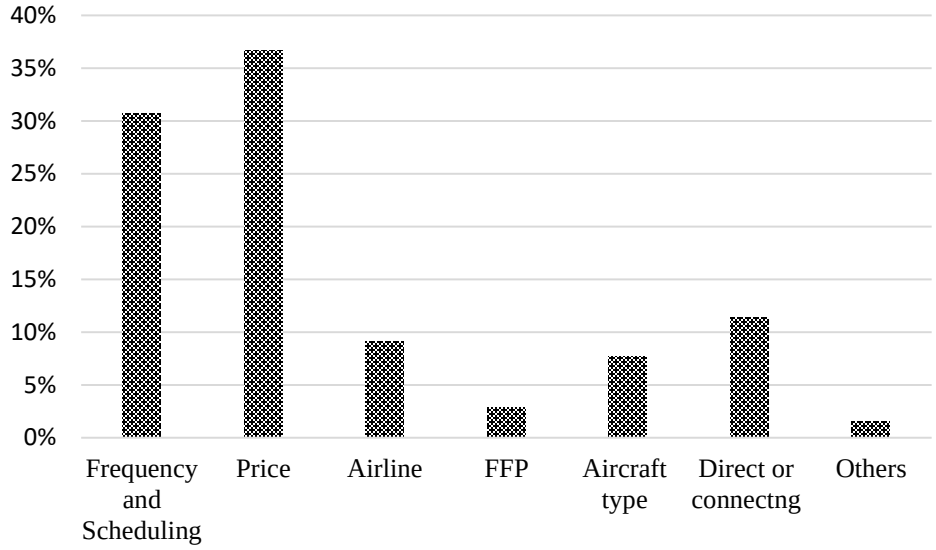
Figure 4.1 Market price elasticity distribution



Note: the IV-2sls is the IV logit model with 2 stage-least square estimation

Chinese air travelers also value high flight frequency. The willingness to pay for one additional flight per week is 3.31 US$ by BLP model (3.53 US$ by our IV regression model). They are very close to the values in Yan and Winston (2014) for the US San Francisco market. The CAMIC (2010) survey reveals that more than 30% of survey respondents in China consider flight scheduling and frequency as the most important factors for their air travel choice, close to the price factor. We also find air passengers in China to value the airline hub status and to be willing to pay for it. Specifically, when airlines fly one more destination, they can charge 0.14 US$ higher per ticket. This finding is also consistent with Yan and Winston (2014). Overall, our demand estimate clearly shows that China has a very similar air travel demand pattern to those of the US.

Figure 4.2 Factors considered by Chinese air passenger for air product choice in the year 2010



Source: CAMIC report 2010.

Note: the percent represents the frequency with which the factor is expressed as the most important factor when the surveyed passengers choose air service product.

4.5.2 Joint estimation of demand and marginal cost functions

The joint estimations of demand and marginal cost are reported in Table 4.4 for the three models with different competition patterns: Bertrand, Cournot and weighted profit. Across the three models, our estimated marginal cost coefficients all seem to have the reasonable signs. The airline marginal cost increases with the distance, more significant for the short-and-medium haul flights. Connecting flight has a lower marginal cost because of the economies of density effects. Airlines also have a lower marginal cost when they have larger scale operations in the endpoint airports. The slot control seems not significant in increasing airlines' marginal cost. We also test other cost specifications, for example, not distinguishing flights by short and long hauls; removing the airport slot control variable; including the airline's number of departures as suggested by Lee (2015).

None of the cost parameter estimates change significantly, suggesting our estimates of marginal cost to be fairly robust.

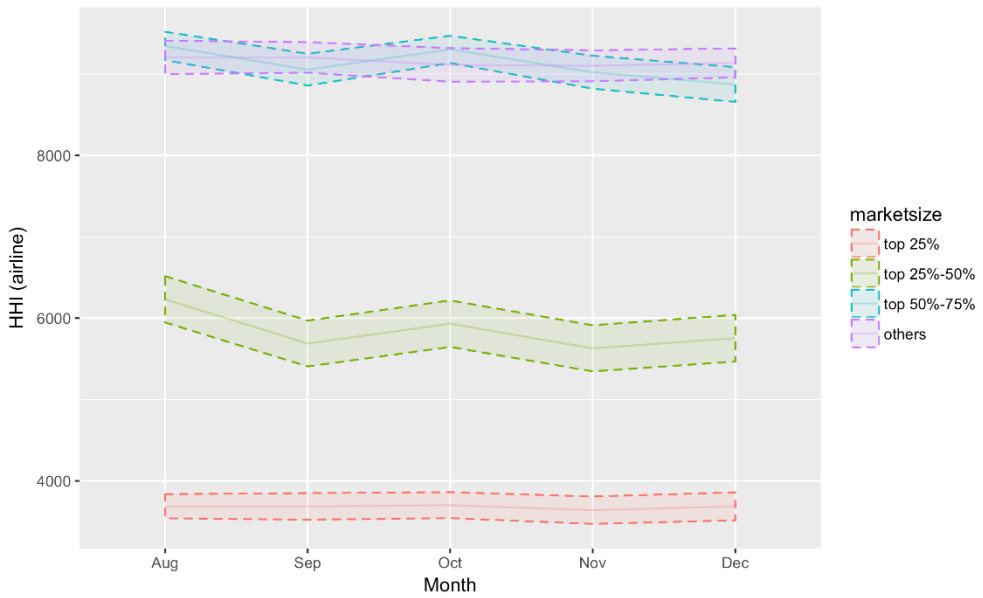
We are most interested in the estimated values of the Lagrangian multiplier vector ϕ under the weighted-profit model. We find for the most densely travelled markets (the top 25%), ϕ_1 is estimated to be 0.45 and statistically significant. This indicates that each airline internalizes almost half of the rivals' profit when making its own pricing decision. For the rest of the route categories, none of the ϕ values is significant. We thus only detect price collusion on the densest domestic routes. This is probably in line with our conjecture that the regulations imposed on the densest routes and the airport slot control by the regulator can lead to airline collusion. On other less traveled routes where regulations are relatively light, Chinese airlines compete intensely close to a Bertrand competition mode. [64]

Figure 4.3 and 4.4 plot the average route-level concentration (the Herfindahl-Hirschman Index) and the average prices for the route markets with different traffic density. The most travelled routes (the top 25%) are much less concentrated because the demand is large enough to sustain more airlines. This probably explains the fact that yields on these routes are actually lower than those on medium-sized routes. There is higher market concentration on the thin routes (e.g. 'other' routes or the bottom 25% least travelled routes), which leads to average yields comparable with those on the most travelled routes. However, our tests on type of competition suggest that there are some degrees of collusion among carriers on the densely travelled routes, which raised price above the level that would have prevailed in a Bertrand competition equilibrium. On the thin routes, airline competition is actually closer to the Bertrand equilibrium. The observed price collusion on the densest market is likely due to regulatory effects instead of self-enforcing cartel, because such

[64] It is possible that the dense routes have lower operating cost due to economies of density, thus contributing to the observed higher profit margin. It is also likely that the dense route can be more congested, raising airline operating cost. To rule out these confounding factors from the cost side, in the airline cost function estimation, we have also controlled for the effects of economies of density and airport congestion on airlines' cost and thus airlines' profit margin. Specifically, the variable "*Hub*" is included in the cost function to capture the economies of density when the routes have large traffic volume when linking major airline hubs in China. The estimation in Table 4.4 indicates that for routes with hub endpoint airport, the marginal operating cost is lower. Besides, the variable "*slot_control*" is included to capture the airport congestion effect on airline operating cost. The sign of this variable is positive in all the estimations, while only significant in Cournot model. After controlling the operating cost differences among dense and thin markets, it is safer to attribute the higher profit margin on the dense routes to airlines' collusive behaviors.

collusion patterns were not detected in other markets, especially those highly concentrated routes that are easier to sustain a cartel.

Figure 4.3 Average route-level airline HHI for different density markets from August to December of 2010

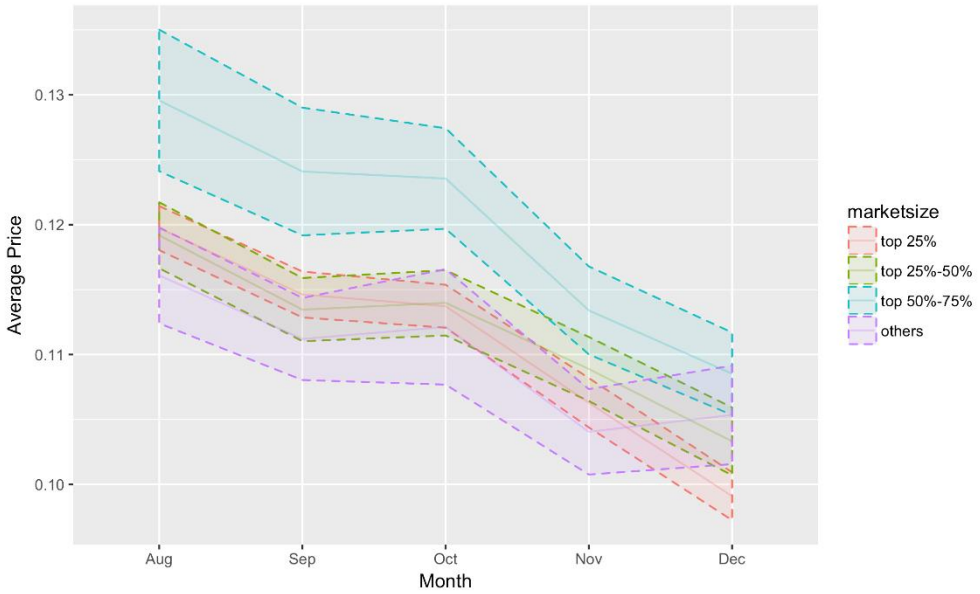


Note:

(1). The regions between dashed lines represent the 95% confidence interval.

(2). The route passenger number is used as weight to calculate the average HHI for each category of markets.

Figure 4.4 Average route-level yield (in USD$) for different density markets from August to December 2010



Note:

(1). The yield is calculated by dividing the airfare with the flying distance.

(2). The regions between dashed lines represent the 95% confidence interval.

(3). The route passenger number is used as weight to calculate the average yield for each category of markets.

As the GMM method relies on a numerical calculation of a weight matrix, which can affect the estimation stability, we also try to use the same numerical weight matrix of the Bertrand, Cournot models for the weighted profit model. Estimates do not significantly change and the price collusion is again detected in the densest routes (i.e. top 25%) but not the others. Although no restriction is put to force the estimated ϕ to be in the sensible range [0, 1], all estimated ϕ are within this range. All these results provide support to the validity of the model and estimation.

Table 4.4 BLP joint estimation of demand and marginal cost functions

Demand Variables	Bertrand Model	Cournot Model	Weighted Profit Model
Fare	-1.2605***	-1.4533***	-0.9232***
	(0.0545)	(0.0554)	(0.0560)
Connection	-1.3205***	-1.34715***	-1.3331***
	(0.0175)	(0.01675)	(0.01705)
Constant	-10.8620***	-10.7260***	-10.8290***
	(0.1113)	(0.1099)	(0.1078)
No. Destination	0.1548***	0.2060***	0.1081***
	(0.0443)	(0.0431)	(0.0436)
No. Departure	0.0275***	0.0269***	0.0286***
	(0.0012)	(0.0012)	(0.0012)
Distance	1.9977***	2.1280***	1.7554***
	(0.1000)	(0.1011)	(0.0992)
Distance_squared	-0.4189***	-0.4230***	-0.4065***
	(0.0306)	(0.0309)	(0.0300)
Tour	0.9326***	0.8264***	0.8811***
	(0.0503)	(0.0499)	(0.0501)
Slot_control	-0.5181***	-0.5004***	-0.5183***
	(0.0358)	(0.0356)	(0.0350)
Income	0.0549***	0.0508***	0.0527***
	(0.0019)	(0.0018)	(0.0019)

Demand Variables	**Bertrand Model**	**Cournot Model**	**Weighted Profit Model**
γ	0.6416	0.6609***	0.6504***
	(0.0093)	(0.0088)	(0.0093)
Cost Variables			
Constant_short	-0.7253***	-0.9119***	-1.0354***
	(0.0463)	(0.0510)	(0.0734)
Distance_short	0.6685***	0.6689***	0.6637***
	(0.0075)	(0.0075)	(0.0076)
Connection_short	-0.0504***	-0.0346***	-0.0500***
	(0.0043)	(0.0044)	(0.0053)
Constant_long	0.1959	0.0832	-0.0380
	(0.1565)	(0.1618)	(0.1781)
Distance_long	0.2392***	0.2097***	0.2233***
	(0.0538)	(0.0546)	(0.0570)
Connection_long	-0.0269	-0.0096	-0.0530***
	(0.0229)	(0.0233)	(0.0252)
Hub	-0.0704***	-0.1316***	-0.0574***
	(0.0163)	(0.0163)	(0.0180)
Slot_control	0.0048	0.0129*	-0.0021
	(0.0088)	(0.0088)	(0.0096)
ϕ_1			**0.4489*** **

Demand Variables	Bertrand Model	Cournot Model	Weighted Profit Model
			(0.2127)
ϕ_2			0.0487
			(0.3450)
ϕ_3			0.3497
			(0.4409)
ϕ_4			0.4592
			(0.4292)

Note: * Significant at the 10% level; **Significant at the 5% level; *** Significant at the 1% level.

Next, we benchmark our weighted profit model with the estimates under the assumption of Bertrand and Cournot competition (henceforth referred to as Bertrand model and Cournot model). Such a "menu" approach (Nevo, 2001) allows us to decide which model is more reasonable. Specifically, we first compare the estimated price elasticities derived from the three models to those obtained from the consistent demand estimation based on the demand moments only. Second, we benchmark the predicted price-cost margins of the three models with our Chinese airlines' accounting data.

Table 4.5 summarizes the estimated values of price elasticities and airlines' price-cost margins. First, the median price elasticity estimated by the weighted profit model is -1.11, very close to the consistent estimate using only the demand moments (1.02 as reported in the last column). The Bertrand and Cournot models, however, over-estimate the price elasticities with values of -1.51 and -1.74, respectively. For the predicted price-cost margins, Cournot model yields higher values than Bertrand model, in line with the theoretical conclusions obtained by Li and Huh (2011). This

is because the quantity competition is overall less intense than price competition.[65] Weighted profit model produces the highest price-cost margin estimates among the three models, which makes sense. Berry and Jia (2010) find the price-cost margin to be about 0.60 for the US domestic markets. [66] Chinese airlines are expected to achieve higher price-cost margin than the US carriers, because airfare levels are comparable in the two countries (see Table 4.6) but Chinese carriers enjoy lower unit operating cost (Wang et al, 2014). Among the three models, only the weighted profit model predicts estimates higher than that in the US market.

In sum, the model incorporating possible legacy regulation effect (weighted profit model) provides better estimates and more reasonable results than the Bertrand and Cournot models. Without explicitly modeling such possible effects of regulation, simply assuming Bertrand or Cournot competition would lead to biased estimates, as discussed above for the cases of demand and airline competition analysis.

[65] It should be cautioned that if products are differentiated, it is possible for some firms to have lower profit margin in Cournot competition than Bertrand competition, because Cournot competition does not necessarily improve every firm's profitability. Hackner (2000) proves that the high-quality firms can earn higher profits under price competition than under quantity competition.

[66] Note in the calculation of price-cost margin marginal cost per flight or passenger is used. Fixed cost such as aircraft capital, depreciation, airport and ground handling cost are not included. That is, only variable costs are included which lead to higher margin at route level.

Table 4.5 Estimated airline profit margin and demand elasticity of the three competition conducts

Profit Margin	Bertrand Model	Cournot Model	Weighted Profit Model	Berry and Jia (2010)
Overall	0.484	0.621	0.660	0.60
Direct Flight	0.531	0.677	0.712	0.66
Connecting Flight	0.377	0.503	0.561	0.56
CA	0.405	0.547	0.592	
MU	0.462	0.599	0.648	
CZ	0.487	0.612	0.650	
HU	0.497	0.634	0.687	
FM	0.461	0.610	0.674	
ZH	0.473	0.632	0.666	
MF	0.509	0.664	0.697	
SC	0.523	0.677	0.712	
Top 25% market			0.684	
25%-50% market			0.644	
50%-75% market			0.628	
other market			0.661	
Price Elasticity	**Bertrand Model**	**Cournot Model**	**Weighted Profit Model**	**Demand Side (BLP)**
Market Aggregate	-1.5113	-1.7405	-1.1092	-1.022

Note:

(1). Berry and Jia (2010) assumes airline Bertrand competition.

(2). the 95% confidence intervals of each profit margin statistic have been obtained using the bootstrap method. They are not reported to save space, but the intervals are very tight so that the profit margins of each model does not overlap with each other.

Table 4.6 Yield comparison between Chinese and US airlines from accounting data

(a) Average yield for different categorized Chinese domestic routes (US$/Kilometer)

Route Category	2008-Q4	2009-Q1	2009-Q2	2009-Q3	2009-Q4	2010-Q1	2010-Q2
Top 1- Top 50	0.096	0.101	0.101	0.118	0.111	0.109	0.122
Top 51- Top 150	0.098	0.105	0.104	0.117	0.110	0.110	0.117
others	0.117	0.119	0.119	0.130	0.124	0.124	0.130
All	0.114	0.117	0.116	0.128	0.122	0.122	0.128

Note: The yield is calculated by dividing ticket price by flying distance. The fare data is from PaxIS; Flying distance is from OAG. The data are for Air China, China Eastern and China Southern airlines only.

(b) Average yield for US Carriers (USD/kilometer)

(c)

Airline Group	2008-Q4	2009-Q1	2009-Q2	2009-Q3	2009-Q4
Regional	0.121	0.117	0.103	0.098	0.104
Low-Cost	0.084	0.075	0.071	0.071	0.078
Network	0.083	0.075	0.068	0.070	0.075
21-Carrier Total	0.085	0.077	0.071	0.071	0.078

Source: Wang et al (2014)

We also conduct a counterfactual analysis by eliminating the collusive pricing on the densest routes. This simulates the hypothetic case in which constraints on airlines, such as the legacy regulation and possible airport slot limits, are removed. We first set ϕ_1=0 for the top 25% routes which correspond to Bertrand competition. The new equilibrium price vector p_t^* is a fixed-point solution to the following first-order condition which is a unique solution (see the proof in Appendix C4).

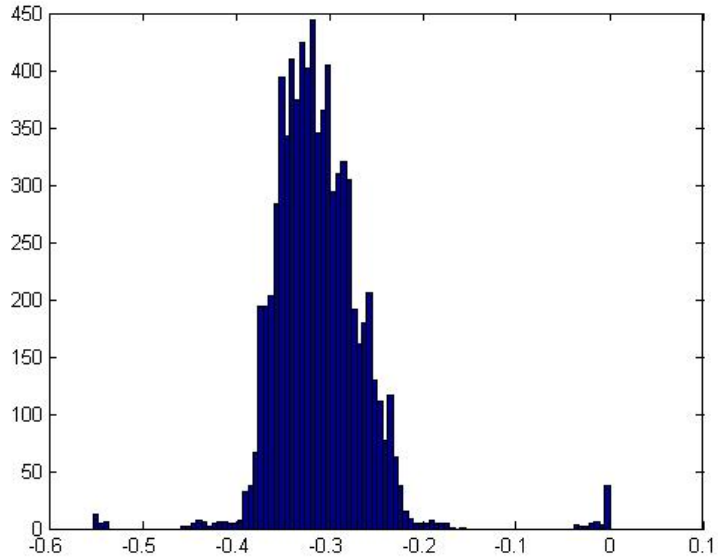
$$p_t = \Omega_t^{-1}(p_t) s_t\left(p_t; x_t, \xi_t, \theta_d\right) + mc_t(\omega_t, w_t, \psi) \tag{4.34}$$

With the initial p_t^0 set to be the current airfare, the new equilibrium price vector is obtained with the following numerical iterations until the convergence defined by Eq. (4.35) is reached. The prices on the top 25% densest routes in the counterfactual case are reduced by 30 US$ on average, which is about one quarter of the current price. The distribution of the price changes is plotted in Figure 4.5. This counterfactual analysis indicates a major gain in consumer surplus if competition can be promoted in these most travelled markets. [67]

$$p_t^M = \Omega_t^{-1}(p_t^{M-1})\, s_t\left(p_t^{M-1}; x_t, \xi_t, \theta_d\right) + mc_t(\omega_t, w_t, \psi) \tag{4.35}$$

[67] However, this counterfactual analysis assumes that air travel product characteristics other than price, such as flight frequency, number of destinations served out of airports, airport slot control, all remain unchanged. In reality, airlines can adjust flight frequency and make changes to network configuration in response to deregulation and airport capacity expansion.

Figure 4.5 Price Reduction distribution by dliminating price collusiveness on Top 25% dense markets (in 100 USD)



4.6 Conclusion and need for further study

Many studies use BLP-type models to analyze airline rivalry under the assumption of Bertrand competition. Such an assumption is unlikely to hold in the presence of market constraints such as legacy regulations and/or airport slot controls. Although the 'menu approach' has been used to test collusive behaviors in selected markets, a specific competition type still needs to be assumed. This study proposes an improved econometric approach that allows for a range of competition types that can be empirically identified for different (groups of) routes. Such generality and flexibility allow us to model possible legacy regulatory effects in the Chinese domestic market. Estimates obtained from the new model are benchmarked to those obtained from models with restrictive assumptions such as Bertrand or Cournot competition, and are compared to airlines' actual financial/accounting data. Overall, we find strong evidence that our new approach performs better than existing models in terms of obtaining better estimation and prediction results. Our study suggests that simply assuming a particular type of competition for a market may lead to biased estimates, especially in the presence of competition/operational constraints. Therefore, it is advisable to conduct empirical tests using an approach similar to that proposed in this study.

In addition to the methodological improvements, our study is among the first to empirically estimate a BLP type model for the airline markets in China. Rich results have been obtained. Specifically, there is clear evidence of collusive pricing among Chinese airlines on the routes with strict legacy regulations and airport congestion, while no significant evidence of collusive pricing is observed on less travelled routes with light regulation. Our demand estimate show that Chinese air passengers exhibit similar preferences as those in developed countries in terms of the price elasticity, valuation of flight frequency and degree of aversion to airport congestion.[68]

Although our study highlights the importance to explicitly model the possible effects of competition/operational constraints such as legacy regulation and airport slot limitation, we have not clearly identified the source and cause of the observed pattern, that is, to what extent do specific constraints affect airline competition and market equilibrium in selected (groups of) routes. This problem could have been addressed if detailed regulatory rules can be obtained for each (groups of) route(s). However, as discussed the existing regulatory policies in the Chinese domestic market are quite ad hoc. We hope our study could lead to more in-depth investigations on this important but under-studied market.

[68] Although these results may be somewhat unexpected given China's lower per capita income compared to developed economy, it is consistent with some of the estimates in previous studies on the same market (see for example, Wang et al. 2014a, Fu et al. 2015a, Wang et al., 2017a). Per a survey of CAMIC (2010), more than half of air travels in China have yearly income over US$ 20,000, and 40% of the passengers' fares are paid by the third-party (e.g. company or government agencies). All these suggest that air travel in China are still mostly consumed by high-income customers who are not be price-sensitive. Thus, a systematic demand estimate is essential for the Chinese airline market.

Chapter 5. Airport pricing when airport congestion affects passengers' concession consumption

5.1 Introduction

Airports generate revenues from both aeronautical and non-aeronautical businesses. The former refer to aeronautical activities related to take-offs and landings, aircraft parking and terminal usage, whereas the latter refer to commercial activities on the airport land and buildings including concession services of retail, food and beverage, car rental, and other non-concessional services such as office and land rentals, car parking and advertising (Oum and Yu, 2004). Concession revenue has become the most important source of many airports' income. For example, the shares of concession revenues were 49%, 27% and 20% of the total revenue for Hong Kong, Atlanta and Copenhagen airports respectively, while the shares of total non-aeronautical revenue for those airports were 76%, 67% and 60%, respectively (ATRS, 2014). For most airports, concession is, by far, the most important non-aeronautical service activity. Given that there is a strong demand complementarity between aeronautical services and concession services (Oum et al., 2004), airports may be regarded as a platform providing a two-sided market which derives revenues from both aeronautical and concession services (Kaiser and Wright, 2006). The implications of the demand complementarity on airports' aeronautical and concession service charges have been discussed extensively (see for example Starkie, 2001; Zhang and Zhang, 2003; Oum et al., 2004; Fu and Zhang, 2010; Zhang et al., 2010).

Due to the substantial growth in air traffic over the last few decades, major airports around the world are operating close to capacity. A natural consequence of airport saturation is congestion. For instance, 21% of the US domestic flights were delayed in 2013, and only 68.4% of Chinese domestic flights departed on time in 2014. Extensive literature has been developed on market mechanisms such as congestion pricing, slot trading and slot allocation to address the increasing airport congestion problem (Brueckner, 2002, 2009; Zhang and Zhang, 2003; Basso and Zhang, 2010; Verhoef, 2010). Most of these studies, however, focus on the effect of airport congestion on air travel demand and airport pricing issues, ignoring the potential impact of congestion on

passengers' concession demand. Furthermore, airport congestion is often referred to as runway congestion, and terminal congestion is often not explicitly taken into account. Interesting exceptions include D'Alfonso et al. (2013), who assume that airport congestion can increase passengers' concession demand due to their longer dwell time in the airport (i.e. the time after completing the security check but before boarding), and Wan et al. (2015), who further distinguish runway- and terminal-related congestions, arguing that the latter can increase concession consumption. Both D'Alfonso et al. (2013) and Wan et al. (2015) assume a positive relation between airport congestion and concession demand because of passengers' longer dwell time in the airport. Despite their modeling of this positive congestion effect on concession demand, the actual pattern of such effects is still ambiguous. Thus, the objective of this chapter is to extend the airport economics literature by establishing a direct analytical and empirical link between airport congestion and concession demand while treating endogeneity between these two variables properly.

Although, in principle, longer dwell time due to congestion may increase passengers' chance to consume concession goods, some consumer behavior studies also find that crowdedness, inconvenience and mental stress can discourage consumers' consumption (Harrell et al., 1980; Yüksel, 2007; Li et al., 2009). In the context of airport concession services, airport congestion, and especially the terminal congestion, deteriorates service quality, responsiveness and friendliness of staff, availability of waiting area and washrooms, cleanliness of the facilities, and ease of finding connecting flights (Yang and Fu, 2015). A recent survey of 15 world's largest airports, found that a 0.1 unit increase, on a 5-point scale, in overall satisfaction of airport quality brings 0.8 USD more concession revenue per enplaned passenger (DKMA, 2013). Bohl (2013) surveyed 294 travelers within the Budapest airport, and found that the airport retail store environment and passengers' time pressure significantly influence their visiting and consumption. In an effort to reconcile these juxtaposing effects, we hypothesize that a nonlinear relationship exists between airport congestion and concession demand, and then analyze such effect on airport optimal aeronautical and concession pricing. This study complements the existing airport pricing studies, especially, by recognizing the possible negative effect of airport congestion on concession demand in the analysis of congestion effect on airport pricing.

The present study first models the concession demand as a function of airport congestion, which in turn is a function of the passenger volume, runway and terminal capacity. By doing so, we can analyze the airport congestion effect on airport pricing by endogenzing its effect on passenger's concession demand. Next, an econometric estimation is conducted to verify the findings obtained from the model. Specifically, a system of equations of the airport demand, aeronautical price, and concession price are estimated, utilizing operational and financial panel data for 61 of the world's largest and congested airports in North America, Asia-Pacific and Europe, from 2008 to 2012.

It should be also noted that the majority of existing airport pricing studies still remain theoretical, and the recent empirical studies have focused exclusively on aeronautical pricing (Bel and Fageda, 2010; Bilotkach et al., 2012; Choo, 2014). Systematic empirical investigation on the determinants of airport concession pricing is lacking. To our knowledge, Van Dender (2007) is the only empirical study that estimates airport's concession pricing equation using panel data of 55 major US airports from 1998 to 2002. Our empirical analysis hopes to extend the work of Van Dender (2007) by explicitly measuring airport congestion effect on concession demand and airport pricing. In addition, our data also include the European and Asia-Pacific airports, thus can shed additional light on the effects of different airports' ownership and governance structures.

The rest of the chapter is organized as follows. In Section 5.2, the airport pricing model is proposed to generate the propositions. In Section 5.3, we specify the system of econometric equations to perform the empirical estimation. This section also discusses the data sources, variable constructions and the estimation strategies. The estimation results are presented in Section 5.4. Section 5.5 summarizes the study.

5.2 Theoretical model

Our airport pricing model draws on the work of Zhang and Zhang (2003, 2010) and D'Aflonso et al. (2013) to assume an aggregate utility of air travel, $B(Q)$, where Q is the airport passenger volume. The market equilibrium is reached at [69]:

$$B'(Q)=p+v\,D(Q,\,K) \tag{5.1}$$

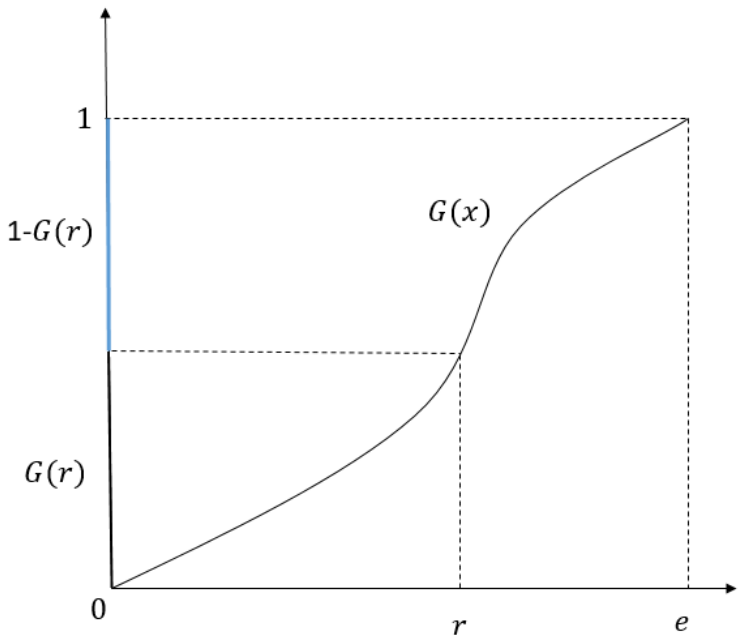
P is the airline ticket price, $v\,D(Q,\,K)$ is the representative passenger's congestion cost, which is a product of the congestion disutility parameter v and airport congestion $D(Q,\,K)$. Airport congestion $D(Q,\,K)$ is a function of airport total passengers Q and airport capacity K. Airport capacity K includes both runway and terminal capacity. Air passengers are assumed to incur congestion disutility from runway flight delay and from terminal congestion. It is assumed that one representative passenger's willingness to pay for the concession service is randomly distributed in a fixed interval $[0, e]$, follows a cumulative distribution function $G(x)$, and a corresponding density function $g(x)$. Airports can decide the concession price r. The probability to consume concession service by the representative consumer is thus $1\text{-}G(r)$, as shown in Figure 5.1. The total airport concession demand is $Q(1\text{-}G(r))$.

This air travel demand specification assumes that air travelers are myopic whose travel decision is primarily driven by the air ticket price not the concession price. This assumption is more widely adopted by most analytical airport pricing studies, recognizing the fact that air travelers may not easily obtain the concession price information before arriving at the airport, or compared to the air ticket price, the concession price is at much smaller amount. There is, however, an emerging literature to account for possible foresight behavior of the air travelers who may consider airport concession price at the travel planning stage (e.g. Czerny, 2006; Bracaglia et al., 2014; Czerny et

[69] In this setup, we assume the marginal passenger indicated by Eq. (5.1) is representative, such that it represents the average utility change of air passengers to the airport congestion, i.e., the dwell time and stress effects. This is a simplification assumption indeed, as passengers can have heterogenous tastes and vary in the response to the dwell time and stress caused by airport congestion. Several studies have considered the impact of different types of passengers on airport pricing and possible discriminating pricing possibly adopted by airports (Czerny and Zhang, 2011, 2014, 2015).

al., 2016; D'Alfonso et al., 2017). This is driven by the easier acquisition of concession price information on airline and booking agencies' websites (bundling products). But this foresight behavior is out of scope this chapter and leaves as a future avenue to explore.

Figure 5.1 The distribution of a representative passenger's willingness to pay for airport concession service



We assume airport congestion to have two countervailing effects on passengers' concession demand. First, congestion leads to longer passenger dwell time which could induce passengers to consume more concession products (Torres et al., 2005; Castillo-Manzano, 2010; D'Alfonso et al., 2013; Wan et al., 2015). Second, congestion leads to greater crowdedness which on the other hand could dampen passengers' willingness to shop due to increasing stress and declining airport service quality (Entwistle, 2007; Bohl, 2013). Combining the abovementioned two effects, we model the congestion effect on concession consumption in the following expression: [70]

[70] In the United States, car rental accounts for a significant proportion of airport concession revenues. Some US airports derive more than half of their concession revenues from car rental services. Airport congestion may have a lower effect on the car rental service than on other concession services, such as food and retail shopping. But severe airport congestion could discourage car rental consumption per person if passengers are worried about the long and unexpected time spent on going through the car rental process.

$$\frac{d\,[1-G(r\,|T(D),S(D)]}{dD}=\underbrace{\frac{\partial(1-G)}{\partial T}}_{>0}\underbrace{\frac{dT}{dD}}_{>0}+\underbrace{\frac{\partial(1-G)}{\partial S}}_{<0}\underbrace{\frac{dS}{dD}}_{>0} \tag{5.2}$$

In Eq. (5.2), T denotes the passenger's dwell time at an airport, and S is the passenger's "stress" from airport congestion. The "stress" is used as a general term to describe airport service quality deterioration and passengers' mental stress from an increased airport congestion. [71] The first term on the right-hand side, $\underbrace{\frac{\partial(1\text{-}G)}{\partial T}}_{>0}\underbrace{\frac{dT}{dD}}_{>0}$, implies that congestion lengthens a passenger's dwell time, and longer dwell time can increase the concession demand [72]. The second term on the right-hand side $\underbrace{\frac{\partial(1\text{-}G)}{\partial S}}_{<0}\underbrace{\frac{dS}{dD}}_{>0}$ implies that congestion also contributes to a passenger's stress, and stress can reduce a passenger's concession demand. Torres et al. (2005) find empirical evidence on a decreasing marginal effect of dwell time on a passenger's concession consumption. Thus, the concession demand per passenger 1-G should be a concave function in T (e.g. $\underbrace{\frac{\partial(1\text{-}G)^2}{\partial^2 T}}_{<0}$). On the other hand, we assume 1-G to be also a concave function of the stress level S (e.g. $\underbrace{\frac{\partial(1\text{-}G)^2}{\partial^2 S}}_{<0}$). This can happen when passengers become increasingly more resistant to consume concession services as they experience more stress or when the service quality deteriorates. In addition, although both dwell time T and stress S increase with congestion D, it is expected that stress S rises faster than dwell time T with the congestion D (equivalent to the elasticity comparison $\frac{d\ln S}{d\ln D} > \frac{d\ln T}{d\ln D}\ |\ D$). This can be true when passengers are more sensitive to the perception of service quality deterioration than the physically increasing dwell time length. Such relation is likely to hold because the longer dwell time per se also contributes to a passenger's stress (Torres et al., 2005).

[71] The stress effect is described to be negative on concession consumption due to airport service quality deterioration and passenger's anxiety to miss the flight. It is possible passengers may consume more concession to relieve stress, but we can attribute this to the dwell time effect.

[72] Here, the dwell time refers to the waiting time of the departing passengers. Therefore, the flight departure delay is more relevant for a longer dwell time. Normally, passenger leaves the airport after landing, thus the arrival delay has little relevance with the dwell time effect.

When airport congestion is low or moderate, we will have $\frac{d\,[1-G(r|T(D),S(D)\,]}{dD} = \underbrace{\frac{\partial(1-G)}{\partial T}}_{>0}\underbrace{\frac{dT}{dD}}_{>0} + \underbrace{\frac{\partial(1-G)}{\partial S}}_{<0}\underbrace{\frac{dS}{dD}}_{>0} > 0$, because $\underbrace{\frac{\partial(1\text{-}G)}{\partial T}}_{>0}$ is significantly larger than $\underbrace{\frac{\partial(1\text{-}G)}{\partial S}}_{<0}$ in absolute magnitude when both T and S are small. Passengers are still feeling relaxed and are willing to consume more concession when staying marginally longer at the airport, leading to $\frac{\partial 1\text{-}G(x,\,D)}{\partial D}>0$ (which is equivalent to the First Order Stochastic Dominance (FOSD) condition, $1-G(x|T(\,D),S(D)) \leq\ 1-G(x|\,T(\bar{D}),S(\bar{D}))$, $\forall\ D<\bar{D}$ and $\forall x\in[0,e]$, which is in line with D'Alfonso et al. (2013)). In this scenario, the dwell time effect dominates the stress effect.

As $\underbrace{\frac{\partial(1-G)^2}{\partial^2 T}}_{<0}$ and $\underbrace{\frac{\partial(1-G)^2}{\partial^2 S}}_{<0}$, when T and S further increase with the congestion D, $\underbrace{\frac{\partial(1\text{-G})}{\partial T}}_{>0}$ turns to be smaller than $\underbrace{\frac{\partial(1\text{-}G)}{\partial S}}_{<0}$ in absolute magnitude. In addition, we also have $\frac{dS^2}{d^2D} \geq \frac{dT^2}{d^2D}\ |\ D$ so that S increases faster than T. Therefore, if airport becomes too congested, the stress effect will turn to dominate the dwell time effect, leading to $\frac{d\,[1\text{-}G(\ T,S\,|\,\mathrm{r})]}{dD} = \underbrace{\frac{\partial(1\text{-}G)}{\partial T}}_{>0}\underbrace{\frac{dT}{dD}}_{>0} + \underbrace{\frac{\partial(1\text{-G})}{\partial S}}_{<0}\underbrace{\frac{dS}{dD}}_{>0} < 0$.[73] This is equivalent to the FOSD condition, $1-G(x|T(\,D),S(D)) \geq\ 1-G(x|\,T(\bar{D}),S(\bar{D}))$, , $\forall\ D>\bar{D}$ and $\forall\ x\in[0,e]$.

To summarize, we should observe the concession demand to have an inverted U-shaped relationship with airport congestion. When congestion is low, dwell time effect outweighs the stress effect such that concession demand increases with airport congestion. But when congestion is high, stress effect becomes dominant, reducing concession demand. [74] Given the fixed airport capacity K, we have the following result as Eq. (5.3):

[73] The increasing congestion at the check-in counters and security check points can also decrease the dwell time for passengers.

[74] However, it should be noted that our assumption is based on a reasonable degree of airport congestion. In reality, in case flights are seriously delayed or even cancelled, passengers may be forced to consume additional meals or to arrange accommodation at the airport. In this way, dwell time effect always dominates stress effect. Nevertheless, such extremely long flight delays should account for a small proportion in airport operations.

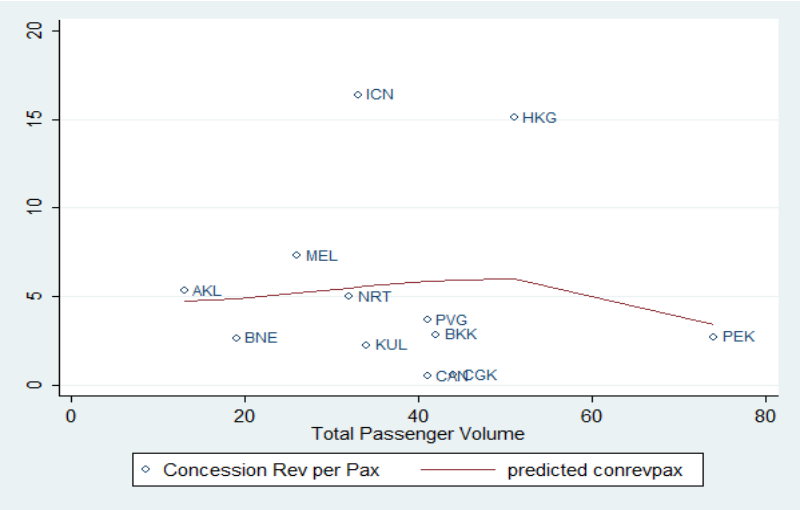
$$\frac{d\,[\,1-G(r\mid T(D(Q,K)),S(D(Q,K)))]}{dQ}=\frac{d\,[1-G(r\mid T(D(Q,K),S\big(D(Q,K)\big))]}{dD(Q,K)}\frac{dD(Q,K)}{dQ} \tag{5.3}$$

Since $\frac{dD(Q,K)}{dQ}>0$, $\frac{d\,[\,1-G(r\mid T(D(Q,K)),S(D(Q,K)))]}{dQ}$ and $\frac{d\,[1-G(r\mid T(D(Q,K),S\big(D(Q,K)\big))]}{dD(Q,K)}$ have the same sign. Thus, given airport capacity K, concession demand also first increases with airport passenger volume and then decreases. The plotted relationship between the airport passenger volume and the airport concession revenue per passenger of our sampled airports appears to support this conjecture. In Figure 5.2, airport concession revenue per passenger seems to exhibit an inverted U-shape with airport passenger volume. However, airport capacity is not controlled. A rigorous investigation is thus called for to verify such prediction.

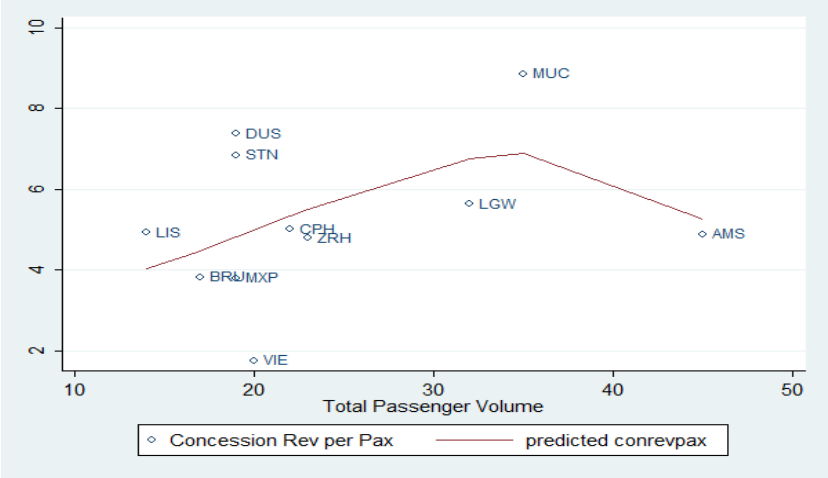
In the above discussion we aggregate the runway and terminal congestion as $D(Q,K)$, and consider how this aggregate congestion affects concession demand. In Appendix D1, we further distinguish runway and terminal congestion, and investigate how runway capacity K_r and terminal capacity K_t can affect concession demand differently. In the remaining part of this section, we examine the impact of dwell time effect and stress effect on airport pricing. To simplify the notation for the next analytical derivation, we will use $1-G(r,D)$ to replace $1-G(r\mid T(D(Q,K),S\big(D(Q,K)\big)$ as the concession demand.

Figure 5.2 Plot of airport passenger volume and concession revenue per passenger

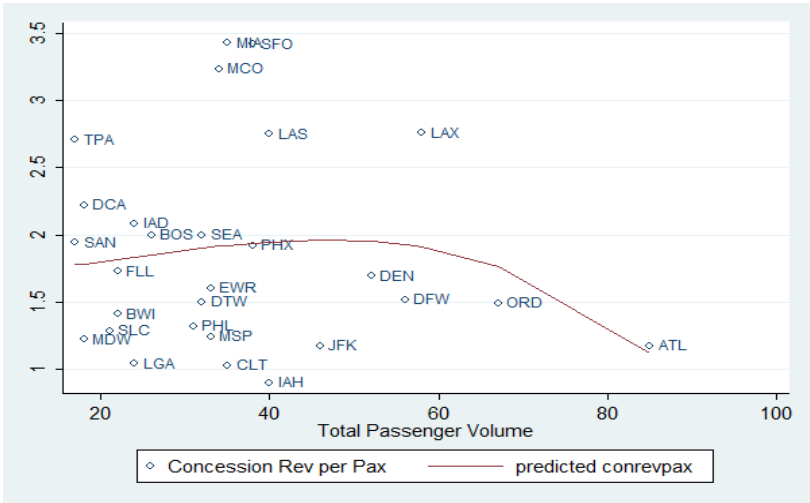
(a). Asian Pacific Airports



(b) European Airports



(c) US Airports



5.2.1 Airline problem

Consider the case where each airline maximizes its profit in a Cournot competition game:

$$\underset{q_i}{\text{Max}} \ (p - c - \tau)\, q_i \tag{5.4}$$

The airline is assumed to be symmetric in cost structure and provides homogenous products, and c denotes the airline marginal operating cost. τ is the airport aeronautical charge to the airline. The First Order Condition (FOC) implies the following:

$$\text{p} = c + \tau - q_i\, B''(Q) + q_i v\, D'(Q,K) \tag{5.5}$$

This is the stylized airline pricing rule in a congested airport. $-q_i B''(Q)$ is the mark-up for the airline market power, and $q_i v\, D'(Q,K)$ is the self-internalization of the congestion cost by the airline. Substituting $p=B'(Q)-v\, D(Q, K)$, indicated by Eq.(5.1), we obtain,

$$\tau = B'(Q) - v\, D(Q,K) - c + \frac{Q}{N}\left(B''(Q) - v\, D'(Q,K)\right) = M(Q) \tag{5.6}$$

From the above derived inverse airport demand function, we can get the derived demand function by converting Eq. (5.6):

$$Q = M^{-1}(\tau) \tag{5.7}$$

Totally differentiating both sides of Eq. (5.6) with respect to τ and rearranging terms we obtain the expression for $\frac{\partial Q}{\partial \tau}$, we have the following Eq. (5.8):

$$\frac{dQ}{d\tau} = \frac{dM^{-1}(\tau)}{d\tau} - \frac{1}{\left(1+\frac{1}{N}\right)\left(v\, D'(Q) - B''(Q)\right) + \frac{Q}{N}\left(v\, D''(Q,K) - B'''(Q)\right)} < 0 \tag{5.8}$$

Eq. (5.8) shows that the airport's derived demand decreases with its aeronautical price τ.

5.2.2 Private Congested Airport

An airport maximizes its profit by choosing both the aeronautical charge τ and the concession price r. The objective of such airport can be formulated as follows:

$$\underset{\tau,\, r}{\text{Max}}\ (\tau - c_1)Q + (r - c_2)\left(1 - G(r, D(Q,K))\right) Q \tag{5.9}$$

where c_1 is the airport marginal operating cost of aeronautical service, and c_2 is the airport marginal operating cost of concession service. From FOC., the aeronautical charge τ can be written as,

$$\tau = c_1 + \left(1+\frac{1}{N}\right)[vQD'(Q,K)B''(Q)Q] + \frac{Q^2}{N}\left(vD''(Q,K) - \mathrm{B'''(Q)}\right) - (r - c_2)$$
$$\left[\left(1 - G(r,D)\right) - Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}\right] \tag{5.10}$$

where $(r\text{-}c_2)[(1\text{-}G(r,D))\text{-}Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}]$ is the term from airport concession operation. If $\frac{\partial G}{\partial D}<0$ (i.e. $\frac{\partial 1\text{-}G}{\partial D}>0$) as we assumed to be the case when airport congestion is low, airport congestion increases the concession demand, making $(r - c_2)\left[\left(1 - G(r,D)\right) - Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}\right]>0$. Therefore, airport concession operation exerts a downward pressure on aeronautical price. But, if $\frac{\partial G}{\partial D}>0$ (i.e., $\frac{\partial 1\text{-}G}{\partial D}<0$), it is possible that $(r\text{-}c_2)\left[\left(1\text{-}G(r,D)\right)\text{-}Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}\right]<0$, such that τ can be higher to reduce congestion so as to increase concession demand.

The optimal r for a private airport is given by:

$$r = c_2 + \frac{1}{\frac{\partial G}{\partial r}}\left(1 - G(r,D)\right) \tag{5.11}$$

The derivative of r with respect to Q is as follows:

$$\frac{\partial r}{\partial Q} = \frac{\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q} + (r - c_2)\frac{\partial^2 G}{\partial r \partial D}\frac{\partial D}{\partial Q}}{-[2\frac{\partial G}{\partial r} + (r - c_2)\frac{\partial^2 G}{\partial r^2}]} \tag{5.12}$$

The denominator is $-\left[2\frac{\partial G}{\partial r}+(r-c_2)\frac{\partial^2 G}{\partial r^2}\right]$<0 from the Second Order Condition (SOC) of airport profit with respect to r. Therefore, when $\frac{\partial G}{\partial D}<0$ and $\frac{\partial^2 G}{\partial r \partial D}$<0, in the case where the concession consumption increases with congestion, we obtain $\frac{\partial r}{\partial Q}>0$. When $\frac{\partial G}{\partial D}>0$ and $\frac{\partial^2 G}{\partial r \partial D}$>0, in the case where the concession consumption increases with congestion, we obtain $\frac{\partial r}{\partial Q}<0$.

5.2.3 Public Congested Airport

The public airport's objective is to maximize social welfare as shown below:

$$\underset{\tau,r}{\text{Max}}\, SW=B(Q)-Qv\,D(Q,K)-(c+c_1)Q+\left(\int_{\mathrm{r}}^{\mathrm{e}} x\frac{g(x,D)}{1\text{-}G(r,D)}dx-c_2\right)(1-G(r,D))Q \tag{5.13}$$

It can be shown that the aeronautical charge τ is equal to:

$$\begin{aligned}\tau=c_1+\frac{Q}{N}B''(Q)+\left(1-\frac{1}{N}\right)vQD'(Q)-[\mathrm{E}(x|\,x>r,\,D)-c_2]\,[1-G(r,D)-Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}]\\ -\left[\frac{\partial D}{\partial Q}\frac{\partial}{\partial D}\mathrm{E}(x\,|x>r,\,D)\right]\big(1-G(r,D)\big)Q\end{aligned} \tag{5.14}$$

$\frac{\partial}{\partial D}\mathrm{E}(x\,|x>r,\,D)$>(<)0 if $\frac{\partial G}{\partial D}$<(>)0. Thus, when congestion is low or moderate, airport concession operation creates a downward pressure on aeronautical price, whereas when congestion is severe, the airport sets a higher aeronautical price to alleviate congestion and to stimulate passengers' concession consumption. The optimal r for public airport is equal to:

$$-rg(r,D)+c_2\frac{\partial G(r,D)}{\partial r}=0 \tag{5.15}$$

Since $\frac{\partial G(r,D)}{\partial r}=g(r,D)$, we thus have $r=c_2$ for a public airport. The concession price is independent of airport congestion level. For public airports, as shown in Appendix D2, we can conclude that $\frac{\partial \tau}{\partial r}<0$ when congestion is low or moderate, and $\frac{\partial \tau}{\partial r}>0$ when congestion is severe. From Eq. (5.10) and Eq. (5.14), we have following Proposition 5.1.

Proposition 5.1. *For both private and public airports, when airport congestion is low or moderate and the concession consumption increases with airport congestion (dwell time effect is dominant), there is a cross-subsidization such that the airport lowers its aeronautical charge to induce a higher traffic volume and a demand increase for concession services. When airport congestion is severe and concession consumption decreases with airport congestion (stress effect is dominant), it is possible for an airport to charge a higher aeronautical price to alleviate congestion and to stimulate concession consumption.*

Proposition 5.1 highlights a possibility for airports to charge a higher aeronautical price in the presence of concession operations. This proposition extends the stylized analytical findings of Zhang and Zhang (2003, 2010), Oum et al. (2004) and Fu and Zhang (2010), and the empirical findings of Choo (2014) on cross-subsidization between aeronautical and concession services. This is because if one acknowledges the adverse stress effect of airport congestion on concession demand, in order to gain optimal profit or social welfare, airports can increase their aeronautical charges to decrease congestion in order to stimulate concession demand.

To compare the aeronautical and concession prices between private and public airports, we present the following set of Propositions 5.2 a and 5.2 b, derived in Appendix D3.

Proposition 5.2 a. *When airport congestion is low or moderate (dwell time effect is dominant), a public airport charges lower aeronautical charges than a private airport. However, when congestion is severe (stress effect is dominant), it is possible for a public airport to charge a higher aeronautical price than a private airport.*

Proposition 5.2 b: *A public airport should charge a lower concession price than a private airport regardless of the airport congestion level.*

Existing research with stylized airport pricing models indicates that private airports charge a higher aeronautical price than public airports (e.g. Zhang and Zhang, 2003). The reasons are twofold. First, as a monopoly, private airports charge a markup on aeronautical price to maximize profit. Second, a welfare maximizing public airport has to lower its aeronautical charges to subsidize airlines with market power in the downstream. Our Proposition 5.2 suggests that when airport congestion can adversely affect passenger concession demand, public airports can have stronger incentives to raise aeronautical charges to alleviate airport congestion so as to guarantee more surplus gain from passengers' concession consumption. It is thus possible for a public airport to set a higher aeronautical price. Such pricing rules narrow the aeronautical price gap between public and private airports. In addition, from Eq. (5.12), we generate the following Proposition 5.3.

Proposition 5.3: *When we model airport congestion as a function of passenger volume, we predict that given airport capacity, airport concession price and passenger volume should have an inverted U-shaped relationship.*

5.3 Empirical estimation

5.3.1 The econometric model

In this section, we carry out an econometric estimation to verify the dwell time and stress effects, and to test our propositions. We refer to our economic model for the variable choices. We also include other factors that are not explicitly included in the theoretical model, such as airport competition and the weather conditions. Log-linear equations are adopted so as to simplify the identification and estimation, while allowing the nonlinearity of functions. Specifically, our system of equations includes: (i). the airport demand equation; (ii). the aeronautical price equation; and

(iii). the concession price equation. The subscript i stands for the airport, j stands for the country, k stands for the continent (North America, Asia-Pacific and Europe), and t stands for the year. Since existing airport data do not allow us to identify the airport concession price, we use the airport concession revenue per passenger, the variable $conrevpax_{ijkt}$, as a proxy. The concession revenue per passenger is equivalent to the term $r(1\text{-}G)$, which is the product of concession price r and individual passenger's probability for concession consumption 1-G. We show in Appendix D4 that our Proposition 5.3 still holds after replacing the concession price r with the concession revenue per passenger term $r(1\text{-}G)$.[75]

Although our propositions are related to airport congestion (the variable D), there is no available data to measure terminal congestion. For runway congestion (which can be measured by airport average flight delay), the data is unavailable for most of the European and Asian airports. Thus, our empirical tests need to rely on airport capacity K and traffic volume Q, since D is a function of K and Q. This functional relation may be implied by plotting the airport flight delay against the number of passengers per runway for our US airports sample whose flight delay data are available. As shown in Figure D1 of Appendix D, the average flight delay in the US airports has a positive linear relationship with the number of passengers per runway. Similarly, since terminal congestion is not directly observable, we also utilize terminal size and passenger number to infer terminal congestion.

The airport demand equation is built based on Eq.(5.6) and Eq. (5.7).

$$\begin{aligned}\ln psgtotal_{ijkt} = \alpha_0 + \alpha_1 \ln aeroatm_{ijkt} + \alpha_2 \ln gdp_{ijkt} + \alpha_3 \ln pop_{ijkt} + \alpha_4 \ln cluster_{ijk} + \\ \alpha_5 \ln dominant_{ijkt} + \alpha_6 LCC_{ijkt} + \alpha_7 \ln intershare_{ijkt} + \phi_{1j} + \eta_{1k} + \nu_{1t} + \psi_{1i} + \varepsilon_{1ijkt}\end{aligned} \tag{5.16}$$

From Eq. (5.7), the airport demand $psgtotal_{ijkt}$ is a function of airport aeronautical price $aeroatm_{ijkt}$. The sign of the parameter α_1 is the price elasticity of derived air travel demand with respect to

[75] From Proposition 5.2 b, we know that a public airport charges a lower concession price r than does a private airport. However, for concession revenue per passenger $r(1\text{-}G(r,D))$, a public airport may have a higher value, since the chance of concession purchase $(1\text{-}G(r,D))$ increases with lower r.

airport aeronautical charge, which should be negative according to Eq. (5.8). Since we assume air travel demand to be independent of airport concession price with "myopic" passengers (Zhang and Zhang, 2003; Oum et al., 2004) as in Eq. (5.1), the concession price does not enter Eq. (5.16). [76] To control for airport competition with nearby airports, we count the number of airports located within 100-km radius for each sampled airport using the variable $cluster_{ijk}$.[77] The variables gdp_{ijkt} and pop_{ijkt} are the GDP and the population of the city where the airport is located. $dominant_{ijkt}$ is the dominant airline's market share in the airport. LCC_{ijkt} is a dummy that captures the presence of LCCs in the airport. Both $dominant_{ijkt}$ and LCC_{ijkt} are used to capture the airline market structure and its impact on airport demand. Finally, $intershare_{ijkt}$ measures the share of international passengers.

The airport aeronautical price equation Eq.(5.17) is based on Eq. (5.10) and Eq. (5.14).

$$\begin{aligned}\ln aerotam_{ijkt} = {} & \beta_0 + \beta_1 \ln psgtotal_{ijkt} + \beta_2 \ln conrevpax_{ijkt} + \beta_3 \ln unitcost_{ijkt} + \beta_4 Public_{ijk} \\ & + \beta_5 \ln runways_{ijkt} + \beta_6 \ln terminalsize_{ijkt} + \beta_7 \ln cluster_{ijk} + \beta_8 \ln pop_{ijkt} + \beta_9 \ln gdp_{ijkt} \\ & + \beta_{10} \ln dominant_{ijkt} + \beta_{11} LCC_{ijkt} + \beta_{12} \ln intershare_{ijkt} + \beta_{13} Pricecap_{ijk} + \beta_{14} ROR_{ijk} \\ & + \beta_{15} Singletill_{ijk} + \beta_{16} Dualtill_{ijk} + \phi_{2j} + \eta_{2k} + v_{2t} + \psi_{2i} + \varepsilon_{2ijkt}\end{aligned} \tag{5.17}$$

To measure aeronautical price, we use the aeronautical revenue per aircraft movement (Bilotkach et al., 2012; Van Dender, 2007).[78] Following Eq. (5.10) and Eq. (5.14), the aeronautical price is a

[76] Czerny (2006) models the airport travel demand as a function of the airport concession price. This implies that passengers, especially business passengers, may well decide upon traveling based on entire trip costs for both tickets and concession price. Czerny et al. (2016), for instance, find empirical evidence that one-dollar increase in daily car rental price reduces 0.36% airport demand by studying 199 US airports.

[77] Small regional airports with yearly passenger number smaller than 150,000 are not counted (Bel and Fageda, 2010).

[78] Airport aeronautical revenue consists mainly of landing charge and terminal fee. The landing charge is on aircraft movement basis, and the terminal fee is normally on per passenger basis. Since the landing charge is the major component of the aeronautical revenue, we use the aeronautical revenue per aircraft movement (ATM) to measure aeronautical price.

function of both airport passenger volume and airport concession price. Proposition 5.1 suggests that the concession price can have different effects on aeronautical price, depending on airport congestion levels. Thus, the sign of β_2 is uncertain. Following Proposition 5.2, public ownership also has a mixed effect on airport aeronautical price, making the sign of β_4 uncertain as well.[79] In addition, we control for the effect of airport price regulations: the price cap, rate-of-return, single-till, and dual-till. The airport concession price equation Eq. (5.18) is based on Eq. (5.11) and Eq. (5.15) and can be written as follows.

$$\begin{aligned}\ln conrevpax_{ijkt} &= \lambda_0 + \lambda_1 \ln psgtotal_{ijkt} + \lambda_2 \ln psgtotal\_2_{ijkt} + \lambda_3 \ln runways_{ijkt} \\ &+ \lambda_4 \ln terminalsize_{ijkt} + \lambda_5 \ln gdp_{ijkt} + \lambda_6 LCC_{ijkt} + \lambda_7 \ln intershare_{ijkt} + \lambda_8 Public_{ijk} \\ &+ \lambda_9 Pricecap_{ijk} + \lambda_{10} ROR_{ijk} + \lambda_{11} Singletill_{ijk} + \lambda_{12} Dualtill_{ijk} \\ &+ \phi_{3j} + \eta_{3k} + \nu_{3t} + \psi_{3i} + \varepsilon_{3ijkt}\end{aligned} \tag{5.18}$$

Proposition 5.3 indicates that concession price has an inverted U-shaped relationship with airport passenger volume. We thus expect a positive λ_1 and negative λ_2 in Eq. (5.18). In Appendix D1, we also show that an increase in runway capacity should negatively affect concession price (a negative λ_3), and larger terminal size should positively affect concession price (a positive λ_4). Airport ownership and price regulation are also controlled for in the concession price equation Eq. (5.18). The proposed system of equations can be re-written as follows.

$$\ln psgtotal_{ijkt} = \alpha_1 \ln aeroatm_{ijkt} + X_{1ijkt}\delta_1 + Z_{1ijkt}\tau_1 + \phi_{1j} + \eta_{1k} + \nu_{1t} + \psi_{1i} + \varepsilon_{1ijkt} \tag{5.19}$$

[79] In order to directly verify Propositions 5.1 and 5.2, we need to incorporate interaction terms between $\ln conrevpax_{ijkt}$, $Public_{ijk}$ and airport congestion variables measured by $\ln psgtotal_{ijkt}$, $\ln runways_{ijkt}$ and $\ln terminalsize_{ijkt}$. The signs of these interaction terms could indicate how airport congestion moderates the effect of concession price and public ownership on aeronautical price, as stated in Propositions 5.1 and 5.2. However, the variables $\ln conrevpax_{ijkt}$, $\ln psgtotal_{ijkt}$ and $\ln terminalsize_{ijkt}$ are all endogenous, making the interaction terms also endogenous in the system of equations. The inclusion of these additional endogenous interaction terms actually fails our identification condition for the aeronautical price equation. Therefore, our estimation of β_2 and β_4 in Eq. (5.17) should be interpreted as the overall effect of concession price and airport public ownership on aeronautical prices, conditional on the average congestion levels among our sample airports.

$$\ln aeroatm_{ijkt}=\beta_1 \ln psgtotal_{ijkt}+\beta_2 \ln conrevpax_{ijkt}+\beta_3 \ln terminalsize_{ijkt}+X_{2ijkt}\,\delta_2 +Z_{2ijkt}\,\tau_2+\phi_{2j}+\eta_{2k}+\nu_{2t}+\psi_{2i}+\varepsilon_{2ijkt} \tag{5.20}$$

$$\ln conrevpax_{ijkt}=\lambda_1 \ln psgtotal_{ijkt}+\lambda_2 \ln psgtotal\_2_{ijkt}+\lambda_4 \ln terminalsize_{ijkt} +X_{3ijkt}\,\delta_3+Z_{3ijkt}\,\boldsymbol{\tau_3}+\phi_{3j}+\eta_{3k}+\nu_{3t}+\psi_{3i}+\varepsilon_{3ijkt} \tag{5.21}$$

These three equations can be written in the following matrix form.

$$\begin{bmatrix} 1 & -\alpha_1 & 0 & 0 & 0 \\ -\beta_1 & 1 & -\beta_2 & -\beta_3 & 0 \\ -\lambda_1 & -\lambda_2 & 1 & -\lambda_4 & -\lambda_2 \end{bmatrix} \boldsymbol{Y_{ijkt}}=\begin{bmatrix} \boldsymbol{X_{1ijkt}} & \boldsymbol{Z_{1ijkt}} \\ \boldsymbol{X_{2ijkt}} & \boldsymbol{Z_{2ijkt}} \\ \boldsymbol{X_{3ijkt}} & \boldsymbol{Z_{3ijkt}} \end{bmatrix} \begin{bmatrix} \delta_1 & \delta_2 & \delta_3 \\ \tau_1 & \tau_2 & \tau_3 \end{bmatrix} + \begin{bmatrix} \phi_{1j}+\eta_{1k}+\nu_{1t}+\psi_{1i}+\varepsilon_{1ijkt} \\ \phi_{2j}+\eta_{2k}+\nu_{2t}+\psi_{2i}+\varepsilon_{2ijkt} \\ \phi_{3j}+\eta_{3k}+\nu_{3t}+\psi_{3i}+\varepsilon_{3ijkt} \end{bmatrix} \tag{5.22}$$

The airport traffic volume, $psgtotal_{ijkt}$, aeronautical price, $aeroatm_{ijkt}$, concession price, $conrevpax_{ijkt}$, are endogenous given their simultaneity relationship indicated in our model. Squared passenger number, $psgtotal\_2_{ijkt}$, is also endogenous as function of airport traffic volume. Terminal size, $terminalsize_{ijkt}$ is also treated as endogenous since airports have some flexibility to adjust it in relatively shorter term through expansion or renovation. Runway capacity instead is more fixed since runway investment is lumpy and takes a long time (Oum and Zhang, 1990; Xiao et al., 2013; Xiao et al., 2017). Thus, the number of runways is treated as exogenous. $\boldsymbol{X_{ijkt}}=[\boldsymbol{X_{1ijkt}}, \boldsymbol{X_{2ijkt}}, \boldsymbol{X_{3ijkt}}, \boldsymbol{Z_{1ijkt}}, \boldsymbol{Z_{2ijkt}}, \boldsymbol{Z_{2ijkt}}]'$ are exogenous variables satisfying the mean independence condition $E[\boldsymbol{X_{ijkt}}\,\boldsymbol{\varepsilon_{ijkt}}]=0$, where $\boldsymbol{\varepsilon_{ijkt}}=[\varepsilon_{1ijkt}, \varepsilon_{2ijkt}, \varepsilon_{3ijkt}]'$. $\boldsymbol{X_{ijkt}}$ are the exogenous variables included in all the three equations, while $\boldsymbol{Z_{ijkt}}$ are the exogenous variables only included in one of the equations so that they can serve as instrument variables for endogenous variables in the other equations. The demand equation, Eq.(5.16), only contains one endogenous variable, the

aeronautical price; aeronautical pricing equation, Eq.(5.17) contains three endogenous variables: airport passenger volume, concession price and terminal size. Concession pricing equation, Eq. (5.18) contains three endogenous variables, airport passenger volume, squared passenger volume and terminal size.

We do not assume mean independence between $\boldsymbol{X_{ijkt}}$ and $\boldsymbol{\phi_j}$, $\boldsymbol{\eta_k}$, $\boldsymbol{v_t}$. Country, continent and year dummies are used to control for the fixed effect of $\boldsymbol{\phi_j}$, $\boldsymbol{\eta_k}$ and $\boldsymbol{v_t}$. However, it is assumed that $E[\boldsymbol{X_{ijkt}}\,\boldsymbol{\psi_i}]=0$, and thus the airport specific unobservables are orthogonal to our independent variables. Yet, because most time-invariant unobservables such as country, continent, and the time-variant year effects have been controlled, the airport specific unobservable $\boldsymbol{\psi_i}$ could be orthogonal to a large degree. [80]

The identification condition is satisfied for each equation. To estimate the equations, we try both a system GMM (three-stage least square) and an equation-by-equation GMM estimation strategies (two-stage least square).[81] For Eq. (5.16), $\boldsymbol{Z_{2ijkt}}$ and $\boldsymbol{Z_{3ijkt}}$ can be used as instruments for the endogenous variable. For Eq. (5.17), $\boldsymbol{Z_{1ijkt}}$ and $\boldsymbol{Z_{3ijkt}}$ can be used as instruments for the endogenous variables. For Eq. (5.18), $\boldsymbol{Z_{1ijkt}}$ and $\boldsymbol{Z_{2ijkt}}$ can be used as instruments for the endogenous variables. To improve efficiency of the estimation, we also include additional exogenous variables, for example, the yearly average rainfall and snowfall of the airports, as instrument variables.

[80] Although a fully fixed effect model (FE) can control for airport specific unobservable ψ_i, thus relaxing the assumption $E[X_{ijkt}\,\psi_i]=0$, the FE model does not allow us to identify coefficients of several time-invariant factors such as ownership and airport regulation.

[81] Three-stage least square (3SLS) is used to estimate the equations simultaneously with the optimal GMM weight matrix incorporating information from all three equations, whereas a two-stage least square (2SLS) method is applied to each equation individually with random effect (RE), which is a GMM method but only utilizing equation-by-equation information. Both 3SLS and 2SLS estimators should be consistent under our assumption, while 3SLS can produce more efficient estimates.

5.3.2 Data description

Air Transport Research Society (ATRS) airport database is our primary source for the detailed airport operational and financial data. It includes a large sample of North American, European and Asia Pacific airports.[82] Specifically, the airport financial data we retrieved include the airport aeronautical revenues, concession revenues and operating expenses. The airport traffic data include the airport total passenger number, cargo volume, aircraft movements and the share of international passengers. The general airport information includes the number of runways, terminal size and airport ownership. Since we study the congested airports, we complement the ATRS data with information gathered from the Airline Business magazine database which collects statistics on the top 100 world busiest airports. These airports are capacity constrained and subject to some degree of airport congestion. We choose the airports that are present in both the ATRS and Airline Business databases for the period 2008-2012, leading to an unbalanced dataset of 253 observations for a total of 61 sample airports (16 Asia-Pacific airports, 13 European airports, and 32 North American airports). The list of the 61 sample airports is provided in Table D1 of Appendix D. All the Asian, European and Canadian airports are categorized as the level 3 slot-coordinated airports by IATA (International Air Transport Association), which means that these airports are highly congested and thus strict rules of slot allocation are required. [83] Some very congested US airports such as JFK, EWR, LAX, MCO, ORD and SFO, are also categorized as Level 2 and 3 slot coordinated by IATA. The other selected US airports also experience considerable congestion problems.

[82] Each year, ATRS collects airport data and performs a due diligence check through the airport annual reports, industry reports and even direct contact with the airports. Since year 2002, ATRS annually publishes the ATRS Global Airport Benchmarking Report ranking the sampled airports around world in operational efficiency. In its annual ATRS World Conference, the award airports were recognized. For the more details about ATRS and its published report and database, please check its official website: http://www.atrsworld.org/.

[83] Based on the IATA's Worldwide Slot Guideline (WSG), Level 2 airports are airports where there is potential for congestion during some periods of the day, week or season which can be resolved by schedule adjustments mutually agreed between the airlines and facilitator. A facilitator is appointed to facilitate the planned operations of airlines using or planning to use the airport. Level 3 airports are airports where capacity providers have not developed sufficient infrastructure, or where governments have imposed conditions that make it impossible to meet demand. A coordinator is appointed to allocate slots to airlines and other aircraft operators using or planning to use the airport as a means of managing the declared capacity.

The Airline Business magazine database reports the market shares of the top three airlines in each airport. Airports with a significantly dominant airline are more likely to face a concentrated downstream airline market, and more likely to be an important hub for the dominant carrier. Our GDP and population data for different countries and regions were obtained from different sources. The population and GDP are collected from the US Bureau of Economic Analysis (BEA) and the US Census Bureau for the US airports, from Statistics Canada for Canadian airports, from EuroStat for European airports, and finally from the OECD and the World Bank databases for airports in the other countries.

Data on airport ownership was also taken from the ATRS database. Among the 61 sample airports, 20 airports are fully or partially privatized. For the airport regulation regimes, we searched for the price regulation types of each airport, i.e. price-cap, rate-of-return (ROR) or light-handed (no specific regulation). We then distinguish the scope of such price regulation assessing whether concession side is included in the price regulation, *i.e.* single-till or dual-till regulation. [84] The civil aviation authority websites, airport annual reports, industry reports, and academic papers on airport regulation were used to collect and verify information on price regulation for our sampled airports. The detailed variable definition and summary statistics are reported in Table 5.1.

[84] In the US instead of the single and dual till regulation, some airports adopt residual cost-plus rule which is equivalent to single-till while other airports adopt a compensatory cost-plus rule which corresponds to dual-till regulation (Oum et al., 2004).

Table 5.1 Summary statistics

Variables	Brief description	Obs.	Mean	Std. Dev.	Min	Max
Endogenous variables						
$psgtotal_{ijkt}$	Total annual passengers in millions	253	35.2	16.3	13.0	90.0
$aeroatm_{ijkt}$	Aeronautical revenue (in USD) per aircraft movement	253	924.4	792.4	130.6	4851.4
$conrevpax_{ijkt}$	Concession revenue (in USD) per passenger	253	3.58	3.27	0.43	19.14
$terminalsize_{ijkt}$	Terminal size (in m^2)	253	3,75,530	251,746	12,888	1,400,000
Exogeneous variables						
gdp_{ijkt}	Annual GDP (billions USD) of the airport metropolitan area	253	339	349	30	1500
pop_{ijkt}	Total population (millions) of the airport metropolitan area	253	7.24	6.65	1.1	35
$cluster_{ijk}$	The number of other airports within 100 km radius area	253	2.22	1.07	1	5
$dominant_{ijkt}$	Market share of the largest dominant airline	253	35.25%	0.132	11.12%	84.92%
LCC_{ijkt}	Dummy (1 = one of the top three dominant carriers is a low-cost carrier)	253	0.241	0.429	0	1
$intershare_{ijkt}$	Share of the international passengers (percentage)	253	37.79%	0.339	0.2%	100%
$unitcost_{ijkt}$	Total operating expenses (USD) per passenger	253	9.40	6.24	1.83	36.36

Variables	Brief description	Obs.	Mean	Std. Dev.	Min	Max
$public_{ijk}$	Dummy (1 = 100% publicly owned airport)	253	0.67	0.47	0	1
$runways_{ijkt}$	The number of runways	253	3.31	1.43	1	7
$pricecap_{ijk}$	Dummy (1 = airport subjected to price-cap regulation; 0 = airport subjected to rate-of-return regulation or no regulation)	253	0.18	0.38	0	1
ROR_{ijk}	Dummy (1 = airport subjected to rate-of-return regulation; 0 = airport subjected to price-cap regulation or no regulation)	253	0.07	0.26	0	1
$singletill_{ijk}$	Dummy (1 = airport adopt single-till approach; 0 = airport adopt dual-till approach or no regulation)	253	0.57	0.50	0	1
$dualtill_{ijk}$	Dummy (1 = airport adopt dual-till approach; 0 = airport adopt single-till approach or no regulation)	253	0.23	0.42	0	1

5.4 Empirical estimation results

Demand equation estimations are summarized in Table 5.2. Aeronautical charge has a negative and statistically significant effect on passenger volume with both two-stage least square (2SLS) and three-stage least square (3SLS) estimations. But the magnitude of the price elasticity estimate is very small, probably because airport charge accounts for only a very small fraction of airline total costs. Airport competition, indicated by the number of nearby airports, also has a significantly negative effect on airport passenger demand. In addition, airline dominance in the airport seems to stimulate airport passenger volume. This result could be attributed to the fact that a major hub can consolidate and connect more passengers. The share of international passengers has a significantly positive effect. GDP and population are found to contribute to higher air travel demand. It is also noted that LCC variable in 3SLS is significantly negative. This is as expected as the demand function is derived from passenger's utility function, and LCC provides inferior service quality compared to full service carrier (FSC) after we have controlled for the other demand variables. [85]

Table 5.2 The estimation for the demand equation

	2SLS		3SLS	
Explanatory Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Aeronautical price	-0.310***	0.089	-0.144**	0.063
GDP	0.536***	0.069	-0.117	0.129
Population	-0.112	0.103	0.368***	0.137
Nearby airports	-0.175*	0.101	-0.222***	0.054
Dominant airline share	0.104*	0.056	0.094*	0.060
LCC	0.004	0.033	-0.174***	0.055
% of international passenger	0.048**	0.023	0.181***	0.028
Year 2009	-0.023	0.015	-0.040	0.056
Year 2010	0.003	0.017	0.013	0.057
Year 2011	0.019	0.019	0.055	0.058
Year 2012	0.029	0.021	0.200***	0.068
EU airports	0.647**	0.329	-0.965***	0.234
NA airports	-0.397**	0.194	-0.251	0.136

[85] The LCC variable may be subject to endogeneity concern as LCC may self-select to enter uncongested airports charging lower airport charges. We have checked the simple correlations between the LCC dummy variable and the airport traffic and number of passenger per runway and terminal size, and airport pricing. And all these correlation values have absolute magnitude smaller than 0.2. There is no strong empirical evidence the LCC presence is due to airline self selection. Instead, it is more likely due to regional unbalanced LCC development condition and local air travel demand structure affecting LCC dominance at one airport.

Note: 1. *** for 1%, ** for 5% and * for 10% significance level.

2. To make a clear expression, the variables that are specified in logarithm form in the estimation are omitted in the table.
3. Coefficients estimates for the country and continent dummies are removed for parsimony.

The estimation results for the aeronautical price equation are reported in Table 5.3. First, the concession price is found to negatively affect aeronautical charges. Overall, airport congestion for our sampled airports has not seriously dampened the concession demand and thus has not motivated the congested airports to charge higher aeronautical price in presence of concession operation (highlighted in Proposition 5.1). Thus, the stylized findings of cross-subsidization between aeronautical and concession prices still hold among our sampled congested airports. In line with Proposition 5.2, public airports appear to charge a lower aeronautical price as indicated by our 3SLS result. Although we assume a public airport to maximize social welfare without cost recovery constraint, in reality, most public airports are supposed to be self-financed and to reach a break-even (Zhang and Zhang, 2010; Yang and Fu, 2015). Such budget constraint imposed upon the public airports can result in a pricing behavior lying between a purely social welfare-maximizing public airport and a purely profit-maximizing private airport. In addition, the airport unit cost is found to be an essential determinant of the aeronautical charge. This contributes an important addition to the existing empirical airport studies (Bel and Fageda, 2010; Bilotkach et. al, 2012; Van Dender, 2007) which were not able to explicitly control for airport cost due to data availability.

From the 3SLS estimation, we find that price-cap regulation lowers airport aeronautical charges, while the effect of the ROR regulation is statistically insignificant. Both single-till and dual-till regulations lower aeronautical price, while single-till has a stronger effect because concession profit is also considered in determining aeronautical pricing. The effects of airport capacity variables, number of runways and terminal size, on airport aeronautical charges are not statistically significant. As in both Bel and Fageda (2010) and Van Dender (2007) we also do not find significant impact of the dominance of airlines on the airport aeronautical charge.

Table 5.3 The estimation for the aeronautical price equation

Explanatory variables	2SLS Coef.	Std. Err.	3SLS Coef.	Std. Err.
Airport passenger volume	1.087	0.847	0.403	0.306
Concession price	-0.642**	0.301	-0.343***	0.111
Unit operating cost	1.321***	0.383	1.279***	0.069
Public ownership	0.716	0.680	-1.730*	0.969
Number of runways	-0.440	0.399	0.144	0.105
Terminal size	-0.035	0.146	-0.224	0.251
Nearby airports	0.213	0.168	-0.027	0.058
Population	-0.209	0.209	-0.162	0.166
GDP	-0.073	0.209	0.132	0.212
Dominant airline share	-0.136	0.152	0.030	0.068
LCC	0.060	0.675	0.140	0.061
% of international passengers	0.072*	0.043	0.159***	0.034
Pricecap regulation	0.287	0.628	-1.754*	0.969
ROR regulation	-0.186	0.789	-0.303	0.555
Singletill regulation	-0.908**	0.447	-0.713***	0.211
Dualtill regulation	-0.873*	0.498	-0.615***	0.173
Year 2009	0.109*	0.057	0.093	0.060
Year 2010	0.120**	0.048	0.104*	0.061
Year 2011	0.121***	0.449	0.092	0.062
Year 2012	0.127**	0.055	0.120	0.078
EU airports	-0.847	0.573	-0.321	0.555
NA airports	-1.337	0.620	0.482	1.043

Note: 1. *** for 1%, ** for 5% and * for 10% significance level.

2. To make a clear expression, the variables that are taken logoritim in the estimation are not specifically claimed in the table.

3. Coefficients estimate for the country and continent dummies are removed for parsimony.

Table 5.4 collates the estimation results of our concession price equation, which help verify the existence of dwell time and stress effects. Both the 2SLS and 3SLS estimations confirm Proposition 5.3. The concession price first increases with airport passenger volume and then decreases, with an existence of the inverted U-shaped relationship between concession price and airport passenger volume given the airport capacity. Using the estimated coefficients, we draw the inverted U-shaped relation between airport passenger volume and concession price as shown in Figure 5.3. The concession price reaches its peak when airport passenger number reaches around 30 million per year. This is about the median passenger volume for our 61 sample airports.

Table 5.4 The estimation of concession pricing equation

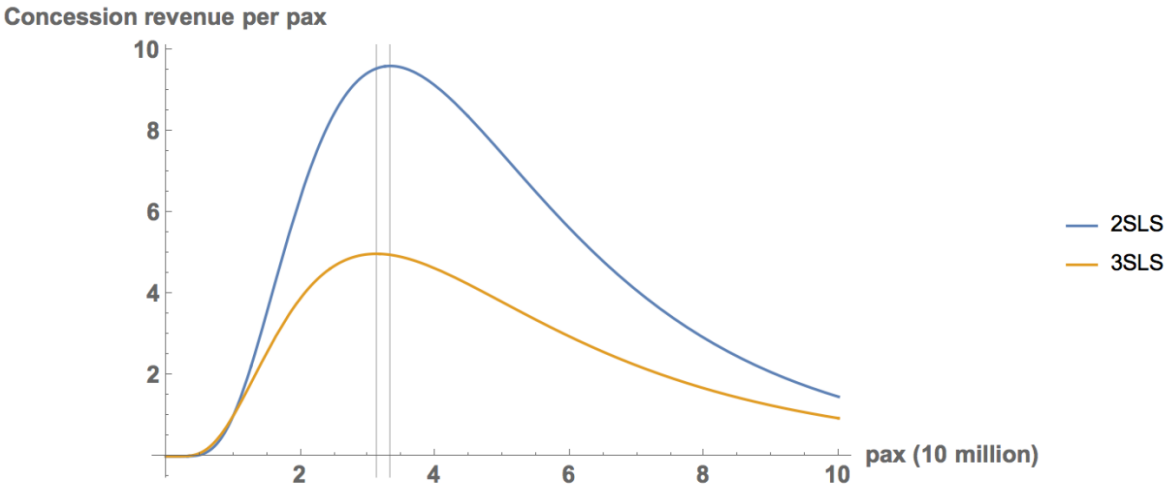
Explanatory variables	2SLS Coef.	2SLS Std. Err.	3SLS Coef.	3SLS Std. Err
Airport passenger volume	3.759***	0.176	2.821**	1.143
Squared passenger volume	-1.560**	0.546	-1.237***	0.422
Terminal Size	0.616***	0.176	0.665***	0.148
Number of runways	-0.435**	0.183	-0.412***	0.155
GDP	0.063	0.074	0.066	0.063
LCC	0.296***	0.100	0.281***	0.086
% of international passengers	-0.163*	0.088	-0.133*	0.072
Public ownership	1.350**	0.649	2.359	1.348
Pricecap regulation	0.716	0.764	1.638**	0.792
ROR regulation	0.776*	0.446	2.040***	0.473
Singletill regulation	-1.530***	0.319	-1.431***	0.266
Dualtill regulation	-1.963***	0.353	-1.872***	0.296
Year 2009	0.001	0.102	-0.016	0.086
Year 2010	-0.081	0.103	-0.086	0.878
Year 2011	-0.039	0.104	-0.041	0.890
Year 2012	-0.061	0.127	-0.053	0.108
EU airports	1.160***	0.375	-0.266	0.497
NA airports	-0.909	0.592	-1.989***	0.597

Note: 1. *** for 1%, ** for 5% and * for 10% significance level.

2. To make a clear expression, the variables that are taken logoritim in the estimation are not specifically claimed in the table.

3. Coefficients estimate for the country and continent dummies are removed for parsimony.

Figure 5.3 Estimated inverted U-shaped curve between airport passenger volume and concession revenue per passenger



The concession price estimations also show that runway capacity has a significantly negative effect on concession price while terminal capacity has a significantly positive effect on concession price. Such results are consistent with the predictions in Appendix D1. Runway congestion contributes mainly to the dwell time effect which increases the concession demand. Terminal congestion is more associated with the stress effect, leading to lower concession demand. In addition, for airports with significant LCC presence, concession price increases, implying a higher concession demand for leisure rather than for business passengers. Higher share of international passengers has a negative effect on concession demand, probably because international flights involve more connection passengers who have time constraint to shop and have no car rental demand. [86]

[86] Unfortunately, we are unable to access the detailed data about the airport transfer-passenger share, preventing us to explicitly control for this flight transfer effect.

5.5 Summary and concluding remarks

This chapter investigates the airport congestion effect on concession demand, and its impact on airports' optimal aeronautical and concession service pricing. In particular, we identify two countervailing effects of airport congestion on concession demand: the dwell time effect and the stress effect. The dwell time effect draws on previous work by D'Alfonso et al. (2013) and Wan et al. (2015) arguing that the airport congestion can lengthen passengers' stay at the airport, and thus, increase their concession consumption. For the first time, this chapter identifies the stress effect, which has a negative effect on concession demand. This stress effect can be attributed to mental stress and service quality deterioration when airports become overcrowded. The empirical evidences of the 61 congested airports worldwide support the existence of both dwell time effect and stress effect.

Because of the presence of the stress factor, we propose and find an inverted U-shaped relation between passenger volume and the concession demand and price. In addition, runway and terminal congestions have opposite effects on concession demand and price. Runway congestion contributes more to the dwell time effect, raising concession demand and price. But terminal congestion generates more stress and thus affects negatively concession demand and price. For the sample covered, the airport concession pricing reaches its peak for a 30-million-passenger airport as revealed by our estimation.

In addition, complementing the existing airport pricing studies, we conclude that, when the stress effect dominates, it is possible for an airport to charge a higher aeronautical price in order to reduce airport congestion, and thereby, to stimulate concession demand. This adds to the stylized findings on the cross-subsidization of aeronautical services by concession operation (Zhang and Zhang, 2003, 2010; Oum et al. 2004). Second, we argue that it is also possible for a public airport to charge higher aeronautical price when the stress effect of airport congestion prevails, contrary to previous studies sustaining a lower aeronautical price for public airports.

This chapter also raises several other issues and avenues for future research. First, we assume that airports directly stipulate concession price. In practice, airports can be the landlord signing rental and revenue sharing contracts with concession service providers such as car rental companies, duty

free stores, and other retail chains. Therefore, the market structure of the concession service providers and the vertical relationships can affect the concession price. However, the data on concession service market structure are not available. Future studies are called for to tackle this issue. Second, because the data on terminal congestion are unavailable, and the runway congestion data are not accessible for the European and Asian airports, we empirically test the congestion effect using the airport capacity and passenger volumes variables. Future studies could be carried out for an accurate measurement of airport terminal congestion, and then directly test the airport congestion effect on airport concession demand and price.

Chapter 6. Conclusion

This dissertation explores three major research topics in transportation economics: (i). seaport investments for adaptation to climate change related disasters; (ii). airline and high-speed rail (HSR) competition; and (iii). airline competition and airport pricing. The dissertation contributes to the related literature by providing rigorous theoretical analysis and empirical evidences to a few important problems that have been overlooked or not well studied. First, we model the port adaptation to climate change related disasters, considering the inter- and intra- port competition and cooperation. More importantly, we adopt the Knightian uncertain to describe the disaster occurrence uncertainty, which is able to capture a more general and wider family of probability distributions, not limited to the specific assumptions in Weitzman (2009) and Xiao et al. (2015). We also explicitly model endogenous port pricing and shippers' demand with port adaptation. The chapter is essential to add to literature by answering how inter-port competition and intra-port cooperation can affect port adaptation besides the impact of disaster uncertainty. We find, with Knightian uncertainty assumption, the port adaptation investments increase with the expectation of the disaster occurrence probability but decrease with its variance. Inter-port competition results in more adaptation investment (i.e., the competition effect). There is free-riding between the port authority and the terminal operator (i.e., the free-riding effect) within each port. Their coordination can increase the adaptation by removing such free-riding effect. The expected social welfare of the two-port region increases with ports' adaptation, such that inter-port competition, and intra-port coordination lead to higher expected social welfare.

The second topic of this dissertation is on the air-HSR competition. Specifically, we investigate, both theoretically and empirically, the effect of HSR speed on airline traffic and price, taking into account the degree of air-HSR service substitutability. This is the first study to explore how airline and HSR service substitutability can alter HSR speed effect on airline traffic and price. We also consider two countervailing effects of HSR speed on airlines, i.e., travel-time and safety effect. The empirical evidence from a rare natural experiment in HSR speed reduction in China is used to empirically verify the theoretical findings. We find that HSR speed effect is stronger when airline and HSR services are more substitutable (i.e., on short-haul routes). The HSR speed effect depends on the relative dominance of travel-time and safety effect. And HSR speed reduction increases

airline traffic and price when travel-time effect dominates, while it reduces airline traffic and price when safety effect dominates.

The last topic addresses two important issues in the air transport economics, namely the airlines competition under legacy regulation, and airport concession pricing with airport congestion. First, a structural discrete-choice model is developed to study airline competition in Chinese domestic market, explicitly taking into account the potential effects of legacy regulation on airlines' competition behavior. This work constitutes an improved econometric approach that allows researchers to identify a range of competitive regimes for different group of routes. This allows us to measure possible effects of the legacy regulation and to benchmark the results obtained under restrictive Bertrand or Cournot competition. We find that Chinese airlines set prices collusively on the densest (with highest traffic volume) routes where regulatory control is stricter and airport congestion is severer; by contrast, they compete more aggressively on less travelled routes with lighter regulatory control. There is also strong evidence that the presented new approach performs better than the existing competition models in terms of obtaining better results on estimation and prediction. This may suggest that simply assuming a particular type of competition regime for a market may yield biased estimation. Second, we explore the effect of airport congestion on airport's concession revenue, and optimal airport pricing on both aeronautical and concession services. We conduct both analytical and empirical investigations, proposing two countervailing effects of airport congestion on concession demand, i.e., dwell-time effect that passengers consume more when airport congestion forces them to stay longer at airport, and the stress effect that passengers are unwilling to spend at airport when they are under stress caused by the flight delay or crowdedness. The optimal aeronautical and concession charges of two types of airports: a private profit-maximizing airport and a public social-welfare maximizing airport are investigated. We find that when airport congestion is severe, and the stress effect prevails, it is possible that public airports charge a higher aeronautical price than private airports. This finding complements previous studies, which ignore airport congestion effect on concession demand and suggest that public airport always charges lower aeronautical price. In addition, empirical evidence supports the existence of both dwell-time and stress effects of airport congestion on concession demand and price. We also find that runway congestion contributes more to dwell time effect while terminal congestion contributes more to stress effect.

This dissertation also opens avenues for future research on several related issues. For the first topic, we assume that each port has a single terminal operator, which could be restrictive. One port can have more than one terminal operator, either private or owned by port authority. Some shipping lines also operate dedicated terminals. In addition, multinational terminal operators such as PSA International, Hutchison Port Holding, APM terminals, DP World and China Merchant Holding can simultaneously operate in several nearby ports. Such intra- and inter-port competition, and inter-port cooperation among private terminal operators can be better accounted for in the future study when analyzing port adaptation. Second, public ownership of port authority and its implication on port adaptation may be also investigated. Although we have explained in Chapter 2 why we focus on private port authorities, the port authority can also be publicly owned and bear social responsibility. It is reasonable to conjecture that public port authority could invest more on adaptation, especially when port adaptation can have positive externality to protect nearby neighborhood community and contribute to a more resilient local economy beyond protecting shippers' economic benefits.

For the second topic, the HSR price is treated as fixed as we are using Chinese market data where government regulates the HSR price. This prevents the investigation on the strategic behavior of HSR. Future study is thus called for on those markets with the HSR being free to decide price. The HSR speed effect on HSR operating cost and its full impact on air-HSR competition can then be identified. Second, we have not considered airline and HSR frequencies adjustment. Yang and Zhang (2012) and D'Alfonso et al (2015) model airline and HSR competing on frequencies. Airline and HSR frequencies are important service quality variables. HSR speed change could also change airline and HSR schedules and frequencies. The frequency and schedule information of airline and HSR in China is difficult to retrieve. Future effort is suggested to take into account frequency and schedule for HSR speed effect estimation.

For the last topic, in Chapter 4, although our econometric model highlights the importance to explicitly model the possible effects of competition/operational constraints such as legacy regulation and airport slot limitation, we have not clearly identified the source of the observed pattern, that is, to what extent do specific constraints affect airline competition and market equilibrium in selected (groups of) routes. This problem could have been addressed if detailed regulatory rules can be obtained for each (groups of) route(s). For the airport congestion on

concession demand and pricing, we assume that airports directly stipulate concession price. In practice, airports can be the landlord signing rental and revenue sharing contracts with concession service providers such as car rental companies, duty free stores, and other retail chains. Therefore, the market structure of the concession service providers and the vertical relationships can affect the concession price. However, the data on concession service market structure are not available. Future studies are called for to tackle this issue. In addition, because the data on terminal congestion are unavailable, and the runway congestion data are not accessible for the European and Asian airports, we empirically test the congestion effect using the airport capacity and passenger volumes variables. Future studies could be carried out for an accurate measurement of airport terminal congestion, and then directly test the airport congestion effect on airport concession demand and price.

References

Adler N., Smilowitz K. (2007). Hub-and-spoke network alliances and mergers: Price-location competition in the airline industry. *Transportation Research part B: Methodological*, 41, 394-409.

Adler, N., Fu, X., Oum, T.H., Yu, C. (2014). Air transport liberalization and airport slot allocation: The case of the Northeast Asian transport market, *Transportation Research - Part A*, 62, 3-19.

Adler, N., Pels, E., Nash, C. (2010). High-speed rail and air transport competition: Game engineering as tool for cost-benefit analysis. T*ransportation Research Part B: Methodological*, 44(7), 812-833.

Aguirregabiria, V., Ho, C. Y. (2012). A dynamic oligopoly game of the US airline industry: Estimation and policy experiments. *Journal of Econometrics*, 168(1), 156-173.

Air Transport Research Society (ATRS) (2014). The ATRS Airport Benchmarking Report: Global Standards for Airport Excellence, 3-Volume Report, Sauder School of Business, University of British Columbia, Vancouver, BC.

Airbus, (2015). Global market forecast 2015-2034. Airbus.

Albalate, D., Bel, G. (2012). High-speed rail: Lessons for policy makers from experiences abroad. *Public Administration Review*, 72(3), 336-349.

Albalate, D., Bel, G., Fageda, X. (2015). Competition and cooperation between high-speed rail and air transportation services in Europe. *Journal of Transport Geography*, 42, 166-174.

Álvarez, A. (2010). Energy consumption and emissions of high-speed trains. Transportation Research Record: *Journal of the Transportation Research Board*, 2159, 27-35.

Andersson, E., Lukaszewicz, P. (2006). Energy consumption and related air pollution for Scandinavian electric passenger trains. Report KTH/AVE 46. Department of Aeronautical and Vehicle Engineering, Royal Institute of Technology, Stockholm, Sweden.

Ashenfelter, O., Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *The Review of Economics and Statistics*, 67, 648-660.

Avenali, A., Bracaglia, V., D'Alfonso, T., Reverberi, P. (2018). Strategic formation and welfare effects of airline-high speed rail agreements. Working paper, Sapienza University of Rome.

Baird, A. J., Valentine, V. F. (2006). Port privatisation in the United Kingdom. *Research in Transportation Economics*, 17, 55-84.

Banister, D., (2011). The trilogy of distance, speed and time. *Journal of Transport Geography*, 19(4), 950-959.

Baron, O., Berman, O. (2014). Nash bargaining with asymmetric bargaining power: Bargaining over profit in a simple supply chain. Working paper, Rotman School of Management, University of Toronto.

Basar, G., Bhat, C.R. (2004). A parameterized consideration set model for airport choice: An application to the San Francisco Bay area. *Transportation Research Part B: Methodological*, 38 (10), 889–904.

Basso, L.J. (2008). Airport deregulation: Effects on pricing and capacity. *International Journal of Industrial Organization*, 26(4), 1015-1031.

Basso, L. J., Zhang, A. (2007). Congestible facility rivalry in vertical structures. *Journal of Urban Economics*, 61(2), 218-237.

Basso, L. J., Zhang, A. (2010). Pricing vs. slot policies when airport profits matter. *Transportation Research Part B: Methodological*, 44(3), 381-391.

Becker, A.H., Acciaro, M., Asariotis, R., Cabrera, E., Cretegny, L., Crist, P., Esteban, M., Mather, A., Messner, S., Naruse, S., Ng, A.K. (2013). A note on climate change adaptation for seaports: a challenge for global ports, a challenge for global society. *Climatic Change*, 120(4), 683-695.

Becker, A., Inoue, S., Fischer, M., Schwegler, B. (2012). Climate change impacts on international seaports: Knowledge, perceptions, and planning efforts among port administrators. *Climatic change*, 110(1), 5-29.

Behrens, C., Pels, E. (2012). Intermodal competition in the London–Paris passenger market: High-Speed Rail and air transport. *Journal of Urban Economics*, 71(3), 278-288.

Bel, G., Fageda, X. (2010). Privatization, regulation and airport pricing: An empirical analysis for Europe. *Journal of Regulatory Economics*, 37(2), 142-161.

Bennett, E.M., Kemler, D., Levin, B.T. (1957). Emotional associations with air and rail transportation. *The Journal of Psychology*, 43(1), 65-75.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25, 242-262.

Berry, S., Carnall, M., Spiller, P.T. (2006). Airline hubs: costs, markups and the implications of customer heterogeneity. In *Advances in Airline Economics: Competition Policy and Antitrust*, Vol. 1, ed. Darin Lee, 183–214. Amsterdam: Elsevier.

Berry, S., Jia, P., (2010). Tracing the woes: an empirical analysis of the airline industry. *American Economic Journal: Microeconomics,* 2, 1-43.

Berry, S., Levinsohn, J, Pakes, A., (1995). Automobile Prices in Market Equilibrium. *Econometrica,* 63(4), 841–90.

Bilotkach, V. (2005). Price competition between international airline alliances. *Journal of Transport Economics and Policy,* 39(2), 167-190.

Bilotkach, V. (2007). Complementary versus semi-complementary airline partnerships. *Transportation Research Part B: Methodological,* 41(4), 381-393.

Bilotkach, V., Clougherty, J.A., Mueller, J., Zhang, A., (2012). Regulation, privatization, and airport charges: panel data evidence from European airports. *Journal of Regulatory Economics,* 42(1), 73-94.

Bilotkach, V., Gorodnichenko, Y., Talavera, O. (2012). Sensitivity of prices to demand shocks: A natural experiment in the San Francisco Bay Area. *Transportation Research Part A: Policy and Practice,* 46(7), 1137-1151.

Binmore, K., Rubinstein, A., Wolinsky, A. (1986). The Nash bargaining solution in economic modelling. *RAND Journal of Economics,* 17, 176-188.

Blainey, S., Hickford, A., Preston, J., (2012). Barriers to passenger rail use: A review of the evidence. *Transport Reviews,* 32(6), 675-696.

Bohl, P. (2013). The impact of airport retail environment on passenger emotions and behavior. Unpublished doctoral dissertation, Corvinus University of Budapest, Budapest, Hungary.

Bonnet, C., Dubois, P. (2010). Inference on vertical contracts between manufacturers and retailers allowing for nonlinear pricing and resale price maintenance. *The RAND Journal of Economics,* 41(1), 139-164.

Borenstein, S. (1989). Hubs and high fares: Dominance and market power in the U.S. airline industry. *The RAND Journal of Economics,* 20, 344-365.

Bosquet, R., Vandanjon, P.O., Coiret, A., Lorino, T. (2013). Model of high-speed train energy consumption. In Proceedings of World Academy of Science, Engineering and Technology (No. 78, p. 1894). World Academy of Science, Engineering and Technology (WASET), January, 2013.

Brander, J. A., Zhang, A. (1990). Market conduct in the airline industry: An empirical investigation. *The RAND Journal of Economics,* 21(4), 567-583.

Brander, J. A., Zhang, A. (1993). Dynamic oligopoly behaviour in the airline industry. *International Journal of Industrial Organization,* 11(3), 407-435.

Bresnahan, T. (1981). Duopoly models with consistent conjectures. *The American Economic Review*, 71(5), 934-945.

Bresnahan, T. (1987). Competition and collusion in the American automobile oligopoly: The 1955 Price War. *Journal of Industrial Economics*, 35, 457-482.

Brida, J.G., Martín, J.C., Román, C., Scuderi, R. (2017). Air and HST multimodal products. A segmentation analysis for policy makers. *Networks and Spatial Economics*, 17(3), 1-24.

Brons, M., Pels, E., Nijkamp, P., Rietveld, P. (2002). Price elasticities of demand for passenger air travel: a meta-analysis. *Journal of Air Transport Management*, 8(3), 165-175.

Brueckner, J.K. (2001). The economics of international code-sharing: An analysis of airline alliances. *International Journal of Industrial Organization*, 19(10), 1475-1498.

Brueckner, J.K. (2002). Airport congestion when carriers have market power. *American Economic Review*, 92(5), 1357-1375.

Brueckner, J.K. (2009). Price vs. quantity-based approaches to airport congestion management. *Journal of Public Economics*, 93(5), 681-690.

Brueckner, J.K., Proost, S. (2010). Carve-outs under airline antitrust immunity. *International Journal of Industrial Organization*, 28(6), 657-668.

Bulow, J.I., Geanakoplos, J.D., Klemperer, P.D. (1985). Multimarket oligopoly: Strategic substitutes and complements. *Journal of Political economy*, 93(3), 488-511.

CAAC (2014). Statistical data on civil aviation of China 2014. Civil Aviation Administration of China (CAAC).

Camerer, C., Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of risk and uncertainty*, 5(4), 325-370.

Capozza, C. (2016). The effect of rail travel time on airline fares: First evidence from the Italian passenger market. *Economics of Transportation*, 6, 18-24.

Castillo-Manzano, J.I. (2010). Determinants of commercial revenues at airports: Lessons learned from Spanish regional airports. *Tourism Management*, 31(6), 788-796.

Chang, S. E. (2000). Disasters and transport systems: loss, recovery and competition at the Port of Kobe after the 1995 earthquake. *Journal of transport geography*, 8(1), 53-65.

Chang, Y. T., Lee, S. Y., Tongzon, J. L. (2008). Port selection factors by shipping lines: Different perspectives between trunk liners and feeder service providers. *Marine Policy*, 32(6), 877-885.

Chen, A. Y., Yu, T. Y. (2016). Network based temporary facility location for the Emergency Medical Services considering the disaster induced demand and the transportation infrastructure in disaster response. *Transportation Research Part B: Methodological*, 91, 408-423.

Chen, H. C., Liu, S. M. (2014). Optimal concession contracts for landlord port authorities to maximise fee revenues. *International Journal of Shipping and Transport Logistics,* 6(1), 26-45.

Chen, Z. (2017). Impacts of high-speed rail on domestic air transportation in China. *Journal of Transport Geography,* 62, 184-196.

Cheon, S., Dowall, D. E., Song, D. W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation research part E: Logistics and transportation review,* 46(4), 546-561.

Choo, Y.Y. (2014). Factors affecting aeronautical charges at major US airports. *Transportation Research Part A: Policy and Practice*, 62, 54-62.

Chou, J.S., Kim, C. (2009). A structural equation analysis of the QSL relationship with passenger riding experience on high speed rail: An empirical study of Taiwan and Korea. *Expert Systems with Applications,* 36(3), 6945-6955.

Chou, J.S., Kim, C., Kuo, Y.C., Ou, N.C., 2011. Deploying effective service strategy in the operations stage of high-speed rail. *Transportation Research Part E: Logistics and Transportation Review*, 47(4), 507-519.

Chou, P.F., Lu, C.S., Chang, Y.H. (2014). Effects of service quality and customer satisfaction on customer loyalty in high-speed rail services in Taiwan. *Transportmetrica A: Transport Science,* 10(10), 917-945.

Ciliberto, F., Williams, J.W. (2014). Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *The RAND Journal of Economics*, 45(4), 764-791.

Civil Aviation Management Institute of China (CAMIC) (2010). An investigation of the market characteristics of civil aviation in 2010. Working paper and industry report (in Chinese).

Clark, D.J., Jørgensen, F., Mathisen, T.A. (2011). Relationships between fares, trip length and market competition. *Transportation Research Part A: Policy and Practice,* 45(7), 611-624.

Clark, D.J., Jørgensen, F., Pedersen, P.A., (2009). Strategic interactions between transport operators with several goals. *Journal of Transport Economics and Policy,* 43(3), 385-403.

Cullinane, K., Ji, P., Wang, T. F. (2005). The relationship between privatization and DEA estimates of efficiency in the container port industry. *Journal of economics and business*, 57(5), 433-462.

Czerny, A.I. (2006). Price-cap regulation of airports: single-till versus dual-till. *Journal of Regulatory Economics*, 30(1), 85-97.

Czerny, A.I., Zhang, A. (2011). Airport congestion pricing and passenger types. Transportation Research Part B: Methodological, 45, 595-604.

Czerny, A.I., Zhang, A. (2014). Airport congestion pricing when airlines price discriminate. *Transportation Research Part B: Methodological*, 65, 77-89.

Czerny, A.I., Zhang, A. 2015. Third-degree price discrimination in the presence of congestion externality. *Canadian Journal of Economics*, 48(4), 1430-1455.

Czerny, A.I., Shi, Z., Zhang, A. (2016). Can market power be controlled by regulation of core prices alone? An empirical analysis of airport demand and car rental price. *Transportation Research Part A: Policy and Practice*, 91, 260-272.

D'Alfonso, T., Jiang, C., Bracaglia, V. (2015). Would competition between air transport and high-speed rail benefit environment and social welfare?. *Transportation Research Part B: Methodological*, 74, 118-137.

D'Alfonso, T., Jiang, C., Bracaglia, V. (2016). Air transport and high-speed rail competition: Environmental implications and mitigation strategies. *Transportation Research Part A: Policy and Practice*, 92, 261-276.

D'Alfonso, T., Jiang, C., Wan, Y. (2013). Airport pricing, concession revenues and passenger types. *Journal of Transport Economics and Policy*, 47(1), 71-89.

De Borger, B., De Bruyne, D. (2011). Port activities, hinterland congestion, and optimal government policies: The role of vertical integration in logistic operations. *Journal of Transport Economics and Policy*, 45(2), 247-275.

De Borger, B., Proost, S. (2012). A political economy model of road pricing. *Journal of Urban Economics*, 71(1), 79-92.

De Monie, G. (2005). Public-private partnership. Lessons at specialization course in public private partnerships in ports' structure, pricing, funding and performance measurement, 10–14 October, ITTMA, Antwerp.

de Neufville, R. (1995). Management of multi-airport systems: A development strategy. *Journal of Air Transport Management*, 2(2), 99-110.

Degryse, H. (1996). On the interaction between vertical and horizontal product differentiation: An application to banking. *The Journal of Industrial Economics,* 44(2), 169-186.

Dixit, A. (1979). A model of duopoly suggesting a theory of entry barriers. *The Bell Journal of Economics,* 10, 20-32.

Dixit, A.K. (1986). Comparative statics for oligopoly. *International Economic Review,* 27(1), 107-122.

DKMA. (2013). Passenger satisfaction: the key to growing non-aeronautical. A consulting report.

Dobruszkes, F. (2011). High-speed rail and air transport competition in Western Europe: A supply-oriented perspective. *Transport policy,* 18(6), 870-879.

Dobruszkes, F., Dehon, C., Givoni, M. (2014). Does European high-speed rail affect the current level of air services? An EU-wide analysis. *Transportation Research Part A: Policy and Practice,* 69, 461-475.

Doi, N., Ohashi, H. (2018). Market structure and product quality: A study of the 2002 Japanese airline merger. *International Journal of Industrial Organization*. In press.

Dresner, M., Lin, J.-S.C., Windle, R. (1996). The impacts of low-cost carriers on airport and route competition. *Journal of Transport Economics and* Policy, 30, 309-328.

Entwistle, M. (2007). Customer service and airport retail: Stimulate passenger spending. *Journal of Airport Management,* 1(2), 151-157.

Everett, S. (2005). Effective corporatization of ports is a function of effective legislation: legal issues in the existing paradigm. In: Proceedings of International Association of Maritime Economists (IAME) 2005 Conference, Limassol, Cyprus, CD-ROM.

Ferreira, R. D. S., Thisse, J. F. (1996). Horizontal and vertical differentiation: The Launhardt model. *International Journal of Industrial Organization,* 14(4), 485-506.

Flores-Fillol, R., Moner-Colonques, R. (2007). Strategic formation of airline alliances. *Journal of Transport Economics and Policy,* 41(3), 427-449.

Franc, P., Van der Horst, M. (2010). Understanding hinterland service integration by shipping lines and terminal operators: A theoretical and empirical analysis. *Journal of Transport* Geography, 18(4), 557-566.

Friedman, J. W. (1971). A non-cooperative equilibrium for supergames. *The Review of Economic* Studies, 38(1), 1-12.

Fu, X., Lei, Z., Wang, K., Yan, J. (2015a). Low cost carrier competition and route entry in an emerging but regulated aviation market–The case of China. *Transportation Research Part A: Policy and Practice,* 79, 3-16.

Fu, X., Lijesen, M., Oum, T.H. (2006). An analysis of airport pricing and regulation in the presence of competition between full service airlines and low cost carriers. *Journal of Transport Economics and Policy,* 40(3), 425-447.

Fu, X., Oum, T.H., Chen, R., Lei Z. (2015b). Dominant carrier performance and international liberalization – the case of Northeast Asia. *Transport* Policy, 43, 61-75.

Fu, X., Oum, T.H., Yan, J. (2014). An analysis of travel demand in Japan's intercity market-empirical estimation and policy simulation. *Journal of Transport Economics and Policy,* 48, 97-113.

Fu, X., Oum T.H., Zhang A. (2010). Air transport liberalization and its impacts on airline competition and air passenger traffic, *Transportation Journal,* 49(4), 24-41.

Fu, X., Zhang, A. (2010). Effects of airport concession revenue sharing on airline competition and social welfare. *Journal of Transport Economics and Policy,* 44, 119-138.

Fu, X., Zhang, A., Lei, Z. (2012). Will China's airline industry survive the entry of high-speed rail? *Research in Transportation Economics,* 35, 13-25.

Furuichi, M., Koppelman, F.S. (1994). An analysis of air travelers' departure airport and destination choice behavior. *Transportation Research Part A: Policy and Practice,* 28(3), 187-195.

Gao, Y., Driouchi, T. (2013). Incorporating Knightian uncertainty into real options analysis: Using multiple-priors in the case of rail transit investment. *Transportation Research Part B: Methodological,* 55, 23-40.

Givoni, M. (2006). Development and impact of the modern high-speed train: A review. *Transport Reviews,* 26(5), 593-611.

Givoni, M., Banister, D. (2012). Speed: The less important element of the high-speed train. *Journal of Transport Geography,* 22, 306-307.

Givoni, M., Dobruszkes, F. (2013). A review of ex-post evidence for mode substitution and induced demand following the introduction of high-speed rail. *Transport Reviews,* 33(6), 720-742.

González-Savignat, M. (2004). Competition in air transport: The case of the high speed train. *Journal of Transport Economic and Policy,* 38, 77-108.

Graham, A. (2009). How important are commercial revenues to today's airports?. *Journal of Air Transport Management,* 15, 106–11.

Hackner, J. (2000). A note on price and quantity competition in differentiated oligopolies. *Journal of Economic Theory,* 93, 233-239.

Haire, A.R., Figliozzi, M.A., Walker, L., MacArthur (2010). Preparing transportation infrastructure for the consequences of climate change: A review of Canadian and US efforts, 8th International Transportation Specialty Conference, Winnipeg, Manitoba.

Harrell, G.D., Hutt, M.D., Anderson, J.C. (1980). Path Analysis of Buyer Behavior under Conditions of Crowding. *Journal of Marketing Research,* XVII, 45-51.

Hess, S., Adler, T., Polak, J.W. (2007). Modelling airport and airline choice behaviour with the use of stated preference survey data. *Transportation Research Part E: Logistics and Transportation Review,* 43(3), 221-233.

Hess, S., Polak, J.W. (2005). Mixed logit modelling of airport choice in multi-airport regions. *Journal of Air Transport Management,* 11(2), 59-68.

Hess, S., Polak, J.W. (2006). Airport, airline and access mode choice in the San Francisco Bay area. *Papers in Regional Science,* 85(4), 543-567.

Hu, W. M., Xiao, J., Zhou, X. (2014). Collusion or Competition? Interfirm Relationships in the Chinese Auto Industry. *The Journal of Industrial Economics,* 62(1), 1-40.

Huang, M., Smilowitz, K. R., Balcik, B. (2013). A continuous approximation approach for assessment routing in disaster relief. *Transportation Research Part B: Methodological,* 50, 20-41.

IPCC (Intergovernmental Panel on Climate Change) (2013). Climate Change 2013: The Physical Science Basis (Summary for Policymakers). Working Group I contribution to the IPCC Fifth Assessment Report, Geneva.

Ishii, J., Jun, S., Van Dender, K. (2009). Air travel choices in multi-airport markets. *Journal of Urban Economics,* 65(2), 216-227.

Ito, H., Lee, D. (2005). Assessing the impact of the September 11 terrorist attacks on US airline demand. *Journal of Economics and Business,* 57(1), 75-95.

Janic, M. (2003). Multicriteria evaluation of high-speed rail, transrapid maglev and air passenger transport in Europe. *Transportation Planning and Technology,* 26(6), 491-512.

Jiang, C., D'Alfonso, T., Wan, Y. (2017). Air-rail cooperation: Partnership level, market structure and welfare implications. *Transportation Research Part B: Methodological,* 104, 461-482.

Jiang, C., Zhang, A. (2014). Effects of high-speed rail and airline cooperation under hub airport capacity constraint. *Transportation Research Part B: Methodological*, 60, 33-49.

Jiang, C., Zhang, A. (2016). Airline network choice and market coverage under high-speed rail competition. *Transportation Research Part A: Policy and Practice*, 92, 248-260.

Kafalenos, R.S., Leonard, K.J. (2008). What are the implications of climate change and variability for gulf coast transportation? In: M.J. Savonis, V.R. Burkett and J.R. Potter (Eds.), Impacts of Climate Change and Variability on Transportation Systems and Infrastructure: Gulf Coast Study, Phase I, Report by the US Climate Change Science Program and the Subcommittee on Global Change Research, Washington, DC: Department of Transportation.

Kaiser, U., Wright, J. (2006). Price structure in two-sided markets: Evidence from the magazine industry. *International Journal of Industrial Organization*, 24(1), 1-28.

Kalai, E., Smordinsky, D. (1975). Other solutions to Nash's bargaining problem. *Econometrica*, 43 513-518.

Kemp, R. (2004). Take the car and save the planet? The environmental impact of rail transport. *Power Engineer*, 18(5), 12-17.

Keohane, R.O., Victor, D.G. (2010). *The regime complex for climate change.* Discussion Paper, The Harvard Project on International Climate Agreements, Cambridge, MA, 2010-33.

Knight, F.H. (1921). Risk, Uncertainty and Profit. Boston: Houghton Mifflin.

Koetse, M.J., Rietveld, P. (2009) The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, 14, 205-221.

Kuo, C.W., Tang, M.L. (2013). Relationships among service quality, corporate image, customer satisfaction, and behavioral intention for the elderly in high speed rail services. *Journal of Advanced Transportation*, 47(5), 512-525.

Lee, J. (2013). Endogenous product characteristics in merger simulation: a study of the U.S. airline industry. Unpublished manuscript.

Li, H., Huh, W.T. (2011). Pricing multiple products with the multinomial logit and nested logit models: concavity and implications. *Manufacturing & Service Operations Management*, 13, 549-563.

Li, J.G.T., Kim, J.O., Lee, S.Y. (2009). An empirical examination of perceived retail crowding, emotions, and retail outcomes. *The Service Industries Journal*, 29(5), 635-652.

Li, Y.T., Schmöcker, J.D. (2017). Adaptation patterns to high speed rail usage in Taiwan and China. *Transportation*, 44, 807-830.

Li, Y.T., Schmöcker, J.D., Fujii, S. (2015). Demand adaptation towards new transport modes: The case of high-speed rail in Taiwan. *Transportmetrica B: Transport Dynamics*, 3(1), 27-43.

Lijesen, M., Behrens, C. (2017). The spatial scope of airline competition. *Transportation Research Part E: Logistics and Transportation Review*, 99, 1-13.

Lin, M.H., Zhang, Y. (2017). Hub-airport congestion pricing and capacity investment. *Transportation Research Part B: Methodological*, 101, 89-106.

Liu, S. M., Chen, H. C., Han, W., Lin, Y. H. (2018). Optimal concession contracts for landlord port authorities to maximize fee revenues with minimal throughput requirements. *Transportation Research Part E: Logistics and Transportation Review*, 109, 239-260.

Liu, Z. (1992). Ownership and productive efficiency: With reference to British ports (Ph.D. thesis). Queen Mary and Westfield College, University of London.

Liu, Z. (1995). The comparative performance of public and private enterprises: the case of British ports. *Journal of Transport Economics and Policy*, 29 (3), 263–274.

Luo, D. (2015). *Airline network-structure change and consumer welfare.* Unpublished manuscript.

Luo, M., Liu, L., Gao, F. (2012). Post-entry container port capacity expansion. *Transportation Research Part B: Methodological*, 46(1), 120-138.

Magala, M., Sammons, A. (2008). A new approach to port choice modelling. *Maritime Economics & Logistics*, 10(1-2), 9-34.

Messner, S., Becker, A., Ng, A. K. (2015). Port adaptation for climate change. In: A.K. Ng, A. Becker. S. Cahoon, S.L. Chen, P. Earl and Z. Yang (Eds.), *Climate Change and Adaptation Planning for Ports*, Routledge: Oxon, United Kingdom.

Min, S., Zwiers, F., Zhang, X., Hegerl, G. (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470, 378–381.

Neven, D., Thisse, J. F. (1990). On quality and variety competition, in Gabszewicz, J. J., Richard, J. F and Wolsey, L. A. (eds), *Economic Decision Making: Games, Econometrics and Optimisation*, Elsevier Science Publishers.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69, 307-342.

Ng, A. K., Becker, A., Cahoon, S., Chen, S. L., Earl, P., Yang, Z. (2016a). Time to act: The criticality of ports in adapting to the impacts posed by climate change. *Climate Change and Adaptation Planning for Ports.* Routledge, 2015.

Ng, A. K., Wang, T., Yang, Z., Li, K. X., Jiang, C (2016b). How is business adapting to climate change impacts appropriately? Insight from the commercial port sector. *Journal of Business Ethics*, DOI 10.1007/s10551-016-3179-6.

Nicholls, R.J., Hanson, S., Herweijer, C., Patmore, N., Hallegatte, S., Corfee-Morlot, J., Chateau, J., Muir-Wood, R. (2008). *Ranking port cities with high exposure and vulnerability to climate extremes: Exposure estimates*. OECD Environment Working Paper No. I, Paris: OECD (http://www.oecdilibrary.org/docserver/download/5kzssgshj 7 42. pdf? expires= 141073 802 9&id=id&accname~guest&c hecksum=FD 11 B404FB7902CDE 156BD3 784524A22).

Nishimura, K. G., Ozaki, H. (2007). Irreversible investment and Knightian uncertainty. *Journal of Economic Theory*, 136(1), 668-694.

Notteboom, T. (2006). Concession agreements as port governance tools. *Research in Transportation Economics*, 17, 437-455.

OECD (2016). Adapting transport to climate change and extreme weather: Implications for infrastructure owners and network managers. Discussion report of International Transport Forum, OECD: Paris.

Oum, T.H., Fu, X. (2007). Air transport security user charge pricing: an investigation of flat per-passenger charge vs. ad valorem user charge schemes. *Transportation Research Part E: Logistics and Transportation Review*, 43(3), 283-293.

Oum, T. H., Waters, W. G., Yong, J. S. (1992). Concepts of price elasticities of transport demand and recent empirical estimates: an interpretative survey. *Journal of Transport Economics and policy*, 26(2), 139-154.

Oum, T.H., Yu, C. (2004). Measuring airports' operating efficiency: a summary of the 2003 ATRS global airport benchmarking report. *Transportation Research Part E: Logistics and Transportation Review*, 40(6), 515-532.

Oum, T. H., Zhang, A., Zhang, Y. (1993). Inter-firm rivalry and firm-specific price elasticities in deregulated airline markets. *Journal of Transport Economics and Policy*, 27(2), 171-192.

Oum, T.H., Zhang, A., Zhang, Y. (1995). Airline network rivalry. *Canadian Journal of Economics*, 28, 836-857.

Oum, T.H., Zhang, A., Zhang, Y. (2004). Alternative forms of economic regulation and their efficiency implications for airports. *Journal of Transport Economics and Policy*, 28, 217–246.

Oum, T. H., Zhang, Y. (1990). Airport pricing: congestion tolls, lumpy investment, and cost recovery. *Journal of Public Economics*, 43(3), 353-374.

Park, J.H. (1997). The effects of airline alliances on markets and economic welfare. *Transportation Research Part E: Logistics and Transportation Review*, 33(3), 181-195.

Park, J.H., Zhang, A. (1998). Airline alliances and partner firms' outputs. *Transportation Research Part E: Logistics and Transportation Review*, 34(4), 245-255.

Pels, E., Nijkamp, P., Rietveld, P. (2000). Airport and airline competition for passengers departing from a large metropolitan area. *Journal of Urban Economics*, 48(1), 29-45.

Pels, E., Nijkamp, P., Rietveld, P. (2001). Airport and airline choice in a multiple airport region: An empirical analysis for the San Francisco Bay Area. *Regional Studies*, 35(1), 1-9.

Pels, E., Nijkamp, P., Rietveld, P. (2003). Access to and competition between airports: A case study for the San Francisco Bay Area. *Transportation Research Part A: Policy and Practice*, 37(1), 71-83.

Pels, E., Verhoef, E. T. (2004). The economics of airport congestion pricing. *Journal of Urban Economics*, 55(2), 257-277.

Postorino, M.N., Pratico, F.G. (2012). An application of the Multi-Criteria DecisionMaking analysis to a regional multi-airport system. *Research in Transportation Business and Management*, 4, 44-52.

Qin, M.S. (2017). *Planes, trains, co-opetition: Evidence from China.* Working paper, University of Minnesota.

Rawls, C. G., Turnquist, M. A. (2010). Pre-positioning of emergency supplies for disaster response. *Transportation research part B: Methodological*, 44(4), 521-534.

Rivers, D., Vuong, Q. (2002). Model selection tests for nonlinear dynamic models. *The Econometrics Journal*, 5(1), 1-39.

Rodrik, D. (1986). Tariffs, subsidies, and welfare with endogenous policy. *Journal of International Economics*, 21(3-4), 285-299.

Schaeffer, M., Hare, W., Rahmstorf, S., Vermeerm, M. (2012). Long-term sea-level rise implied by 1.5_C and 2_C warming levels. *Nature Climate Change*, 2, 867–870.

Schipper, Y., Rietveld, P., Nijkamp, P. (2002). European airline reform: an empirical welfare analysis. *Journal of Transport Economics and Policy*, 36(2), 189-209.

Scott, H., McEvoy, D., Chhetri, P., Basic, F., Mullett, J. (2013). Climate change guidelines for ports. National Climate Change Adaptation Research Facility, Melbourne.

Sheu, J. B. (2014). Post-disaster relief–service centralized logistics distribution with survivor resilience maximization. *Transportation research part B: Methodological*, 68, 288-314.

Singh, N., Vives, X. (1984). Price and quantity competition in a differentiated duopoly. *The RAND Journal of Economics*, 15(4), 546-554.

Socorro, M.P., Betancor, O. (2010). The welfare effects of the allocation of airlines to different terminals. *Transportation Research Part E: Logistics and Transportation Review*, 46(2), 236-248.

Socorro, M.P., Viecens, M.F. (2013). The effects of airline and high speed train integration. *Transportation research Part A: policy and practice*, 49, 160-177.

Starkie, D. (2001). Reforming UK airport regulation. *Journal of Transport Economics and Policy*, 35, 119–135.

Stenek, V., Amado, J., Connell, R., Palin, O., Wright, S., Pope, B., Hunter, J., McGregor, J., Morgan, W., Stanley, B., Washington, R. (2011). *Climate risk and business-ports; Terminal Marítimo Muelles el Bosque, Cartagena, Colombia, Executive Summary*. International Finance Corporation, Washington, DC, 24.

Sudhir, K. (2001). Competitive pricing behavior in the auto market: a structural analysis. *Marketing Science*, 20, 42-60.

Takebayashi, M. (2012). Managing the multiple airport system by coordinating short/long-haul flights. *Journal of Air Transport Management*, 22, 16-20.

Takebayashi, M. (2015). Multiple hub network and high-speed railway: Connectivity, gateway, and airport leakage. *Transportation Research Part A: Policy and Practice*, 79, 55-64.

Takebayashi, M. (2016). How could the collaboration between airport and high speed rail affect the market? *Transportation Research Part A: Policy and Practice*, 92, 277-286.

Takebayashi, M. (2018). Managing airport charges under the multiple hub network with high speed rail: Considering capacity and gateway function. *Transportation Research Part A: Policy and Practice*, in press.

Takebayashi, M., Onishi, M. (2018). Managing reliever gateway airports with high-speed rail network. Working paper, Kobe University.

Talebian, A., Zou, B. (2016). A multi-stage approach to air-rail competition: Focus on rail agency objective, train technology and station access. *Journal of Rail Transport Planning & Management*, 6(1), 48-66.

Terpstra, I., Lijesen, M.G. (2015). The impact of high speed rail on airport competition. *Tijdschrift voor economische en sociale geografie*, 106(3), 263-275.

Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice*, 40(8), 621-638.

Tirole, J. (1988). The theory of industrial organization. MIT press.

Tongzon, J. L. (2009). Port choice and freight forwarders. *Transportation Research Part E: Logistics and Transportation Review*, 45(1), 186-195.

Torres, E., Dominguez, J.S., Valdes, L., Aza, R. (2005). Passenger waiting time in an airport and expenditure carried out in the commercial area. *Journal of Air Transport Management*, 11(6), 363-367.

Trujillo, L., Nombela, G. (2000). Seaports. In: Estache, A., De Rus, G. (Eds.), Privatization and regulation of transport infrastructure guidelines for policymakers and regulators. The world Bank, Washington, D.C., 113–169.

UIC (2017). *High speed lines in the world. International union of railways*. Retrieved at http://uic.org/IMG/pdf/high_speed_lines_in_the_world.pdf.

UNCTAD (2017). Review of Maritime Transport 2017. United Nations Conference on Trade and Development (UNCTAD). UNCTAD

Van Dender, K. (2007). Determinants of fares and operating revenues at US airports. *Journal of Urban Economics*, 62(2), 317-336.

Verhoef, E.T. (2010). Congestion pricing, slot sales and slot trading in aviation. *Transportation Research Part B: Methodological*, 44(3), 320-329.

Vives, X. (1999). Oligopoly pricing: Old ideas and new tools. MIT Press. Cambridge, MA.

Wan, Y., Basso, L.J., Zhang, A. (2016). Strategic investments in accessibility under port competition and inter-regional coordination. *Transportation Research Part B: Methodological*, 93, 102-125.

Wan, Y., Ha, H.K., Yoshida, Y., Zhang, A. (2016). Airlines' reaction to high-speed rail entries: Empirical study of the Northeast Asian market. *Transportation Research Part A: Policy and Practice*, 94, 532-557.

Wan, Y., Jiang, C., Zhang, A. (2015). Airport congestion pricing and terminal investment: Effects of terminal congestion, passenger types, and concessions. *Transportation Research Part B: Methodological*, 82, 91-113.

Wan, Y., Zhang, A., Li, K.X. (2017). Port competition with accessibility and congestion: A theoretical framework and literature review on empirical studies. *Maritime Policy & Management*, 45(2), 239-259.

Wang, K., Fan X., Fu X., Zhou Y. (2014a). Benchmarking the performance of Chinese airlines: an investigation of productivity, yield, and cost competitiveness. *Journal of Air Transport Management*, 38, 3-14.

Wang, K., Fu, X., Luo, M. (2015). Modeling the impacts of alternative emission trading schemes on international shipping. *Transportation Research Part A: Policy and Practice*, 77, 35-49.

Wang, K., Gong, Q., Fu, X., Fan, X. (2014b). Frequency and aircraft size dynamics in a concentrated growth market: The case of the Chinese domestic market. *Journal of Air Transport Management*, 36, 50-58.

Wang, K., Ng, A. K., Lam, J. S. L., Fu, X. (2012). Cooperation or competition? Factors and conditions affecting regional port governance in South China. *Maritime Economics & Logistics*, 14(3), 386-408.

Wang, K., Xia, W., Zhang, A. (2017a). Should China further expand its high-speed rail network? Consider the low-cost carrier factor. *Transportataion Research Part A: Policy and Practice*, 100, 105-120.

Wang, K., Zhang, A., Zhang, Y. (2018). Key determinants of airline pricing and air travel demand in China and India: Policy, ownership, and LCC competition. *Transport Policy*, 63, 80-89.

Wang, Y., Yan, X., Zhou, Y., Xue, Q. (2017b). Influencing mechanism of potential factors on passengers' long-distance travel mode choices based on structural equation modeling. *Sustainability*, 9(11), 1943.

Wei, F., Chen, J., Zhang, L. (2017). Demand shocks, airline pricing, and high-speed rail substitution: Evidence from the Chinese Market. *Journal of Transport Economics and Policy*, 51(4), 266-289.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, 91(1), 1-19.

Wiegmans, B. W., Hoest, A. V. D., Notteboom, T. E. (2008). Port and terminal selection by deep-sea container operators. *Maritime Policy & Management*, 35(6), 517-534.

Windle, R., Dresner, M. (1995). Airport choice in multiple-airport regions. *Journal of Transportation Engineering*, 121(4), 332-337.

Windle, R., Dresner, M. (1999). Competitive responses to low cost carrier entry. *Transportation Research Part* E, 35, 59-75

World Bank (2001). World Bank Port Reform Toolkit Modules 1-8. Washington, DC.

Xia, W., Zhang, A. (2016). High-speed rail and air transport competition and cooperation: A vertical differentiation approach. *Transportation Research Part B: Methodological*, 94, 456-481.

Xia, W., Zhang, A. (2017). Air and high-speed rail transport integration on profits and welfare: Effects of air-rail connecting time. *Journal of Air Transport Management*, 65, 181-190.

Xiao, Y. B., Fu, X., Ng, A. K., Zhang, A. (2015). Port investments on coastal and marine disasters prevention: Economic modeling and implications. *Transportation Research Part B: Methodological*, 78, 202-221.

Xiao, Y., Fu, X., Oum, T.H., Yan, J. (2017). Modeling airport capacity choice with real options. *Transportation Research Part B: Methodological*, 100, 93-114.

Xiao, Y., Fu, X., Zhang, A. (2013). Demand uncertainty and airport capacity choice. *Transportation Research Part B: Methodological*, 57, 91–104

Xiao, Y., Fu, X., Zhang, A. (2013). Demand uncertainty and airport capacity choice. *Transportation Research Part B: Methodological*, 57, 91-104.

Yan, J., Winston, C. (2014). Can private airport competition improve runway pricing? The case of San Francisco Bay area airports. *Journal of Public Economics*, 115, 146-157.

Yang, H., Fu, X. (2015). A comparison of price-cap and light-handed airport regulation with demand uncertainty. *Transportation Research Part B: Methodological*, 73, 122-132.

Yang, H., Zhang, A. (2012). Effects of high-speed rail and air transport competition on prices, profits and welfare. *Transportation Research Part B: Methodological*, 46(10), 1322-1333.

Yang, H., Zhang, A., Fu, X. (2015). Determinants of airport–airline vertical arrangements: Analytical results and empirical evidence. *Journal of Transport Economics and Policy*, 49(3), 438-453.

Yang, Z., Ng, A. K., Lee, P. T. W., Wang, T., Qu, Z., Rodrigues, V. S., Pettit, S, Harris, I., Zhang, D., Lau, Y. Y. (2017). Risk and cost evaluation of port adaptation measures to climate change impacts. *Transportation Research Part D: Transport and Environment*, in press.

Yüksel, A. (2007). Tourist shopping habitat: Effects on emotions, shopping value and behaviours. *Tourism management*, 28(1), 58-69.

Zhang, A., Boardman, A.E., Gillen, D., Waters II, W.G. (2004). *Towards estimating the social and environmental costs of transportation in Canada*. Research Report for Transport Canada, Ottawa, Ontario.

Zhang, A., Chen, H. (2003). Evolution of China's air transport development and policy towards international liberalization. *Transportation Journal*, 42, 32-49.

Zhang, A., Fu, X., Yang, H.G. (2010). Revenue sharing with multiple airlines and airports. *Transportation Research Part B: Methodological*, 44(8), 944-959.

Zhang, A., Zhang, Y. (2003). Airport charges and capacity expansion: effects of concessions and privatization. *Journal of Urban Economics*, 53, 53–75.

Zhang, A., Zhang, Y. (2006a). Rivalry between strategic alliances. International *Journal of Industrial Organization*, 24(2), 287-301.

Zhang, A., Zhang, Y. (2006b). Airport capacity and congestion when carriers have market power. *Journal of Urban Economics*, 60(2), 229-247.

Zhang, A., Zhang, Y. (2010). Airport capacity and congestion pricing with both aeronautical and commercial operations. *Transportation Research Part B: Methodological*, 44(3), 404-413.

Zhang, F., Graham, D.J., Wong, M.S.C. (2017). *Quantifying the substitutability and complementarity between high-speed rail and air transport.* Working paper, Imperial College London.

Zhang, H., Ng, A. K., Becker, A. (2017). A critical discussion on the roles of institutions on ports' adaptation to the impacts posed by climate change. In *Climate Change Adaptation in North America* (pp. 105-117). Springer International Publishing.

Zhang, Q., Yang, H., Wang, Q. (2017). Impact of high-speed rail on China's big three airlines. *Transportation Research Part A: Policy and Practice*, 98, 77-85.

Zhang, Q., Yang, H., Wang, Q., Zhang, A. (2014). Market power and its determinants in the Chinese airline industry. *Transportation Research Part A: Policy and Practice*, 64, 1-13.

Zhang, R., Johnson, D., Zhao, W., Nash, C. (2018). Air pricing and frequencies in the presence of HSR in China. *Transportation Research Part A: Policy and Practice,* forthcoming.

Zhang, Y., Lam, J. S. L. (2015). Estimating the economic losses of port disruption due to extreme wind events. *Ocean & Coastal Management*, 116, 300-310.

Zhang, Y., Round, D.K. (2011). Price wars and price collusion in China's airline markets. *International Journal of Industrial Organization*, 29(4), 361-372.

Appendices

Appendix A: Appendix for Chapter 2

A.1 Optimal terminal operators' prices and port authorities' concession fee

For the competing port authorities, the FOCs satisfy $\frac{\partial \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i} = 0$. For the monopoly port authority, the FOCs satisfy $\underbrace{\frac{\partial \pi_i(\tilde{\phi}_i,\tilde{\phi}_j)}{\partial \phi_i}}_{<0} + \underbrace{\frac{\partial \pi_j(\tilde{\phi}_i,\tilde{\phi}_j)}{\partial \phi_i}}_{>0} = 0$. With the monopoly port authority setting concession fee at one port, it internalizes the positive externality of higher concession fee on the other port i.e. $\underbrace{\frac{\partial \pi_j(\tilde{\phi}_i,\tilde{\phi}_j)}{\partial \phi_i}}_{>0}$ and $\underbrace{\frac{\partial \pi_i(\tilde{\phi}_i,\tilde{\phi}_j)}{\partial \phi_j}}_{>0}$. In addition, the second-order derivative $\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i \partial \phi_j} > 0$, as concession fee at ports is strategic complement. The second-order derivative $\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial {\phi_i}^2} < 0$ as required by SOC. Because of the symmetry, we have $\tilde{\phi}_i = \tilde{\phi}_j$ and $\bar{\phi}_i = \bar{\phi}_j$. In magnitudes it is true that $\left|\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial {\phi_i}^2}\right| > |\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i \partial \phi_j}|$. In other words, the second-order derivative $\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial {\phi_i}^2}$ is the main effect. Because $\frac{\partial \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i} = 0$ and $\frac{\partial \pi_i(\tilde{\phi}_i,\tilde{\phi}_j)}{\partial \phi_i} < 0$, we have $\tilde{\phi}_i = \tilde{\phi}_i > \bar{\phi}_i = \bar{\phi}_j$. Terminal operators' charge $p_i(\phi_i, \phi_j)$ and $p_j(\phi_i, \phi_j)$ are increasing function of ϕ_i and ϕ_j, such that $\tilde{p}_i(\tilde{\phi}_i, \tilde{\phi}_i) > \tilde{p}_i(\bar{\phi}_i, \bar{\phi}_j)$ and $\tilde{p}_j(\tilde{\phi}_i, \tilde{\phi}_i) > \tilde{p}_j(\bar{\phi}_i, \bar{\phi}_j)$.

Taking total derivatives of FOCs of competing port authorities with respect to I_i^a:

$$\frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i \partial I_i^a} + \frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial {\phi_i}^2}\frac{\partial \bar{\phi}_i}{\partial I_i^a} + \frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i \partial \phi_j}\frac{\partial \bar{\phi}_j}{\partial I_i^a} = 0$$

$$\frac{\partial^2 \pi_j(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_j \partial I_i^a} + \frac{\partial^2 \pi_i(\bar{\phi}_i,\bar{\phi}_j)}{\partial \phi_i \partial \phi_j}\frac{\partial \bar{\phi}_i}{\partial I_i^a} + \frac{\partial^2 \pi_j(\bar{\phi}_i,\bar{\phi}_j)}{\partial {\phi_j}^2}\frac{\partial \bar{\phi}_j}{\partial I_i^a} = 0$$

Solving $\frac{\partial \bar{\phi}_i}{\partial I_i^a}$ as follows:

$$\frac{\partial \bar{\phi}_i}{\partial I_i^a} = \frac{-(\frac{\partial^2 \pi_j}{\partial {\phi_j}^2}\frac{\partial^2 \pi_i}{\partial \phi_i \partial I_i^a}) + \frac{\partial^2 \pi_i}{\partial \phi_i \partial \phi_j}\frac{\partial^2 \pi_j}{\partial \phi_j \partial I_i^a}}{\frac{\partial^2 \pi_i}{\partial {\phi_i}^2}\frac{\partial^2 \pi_j}{\partial {\phi_j}^2} - \frac{\partial^2 \pi_i}{\partial \phi_i \partial \phi_j}\frac{\partial^2 \pi_j}{\partial \phi_i \partial \phi_j}} > 0$$

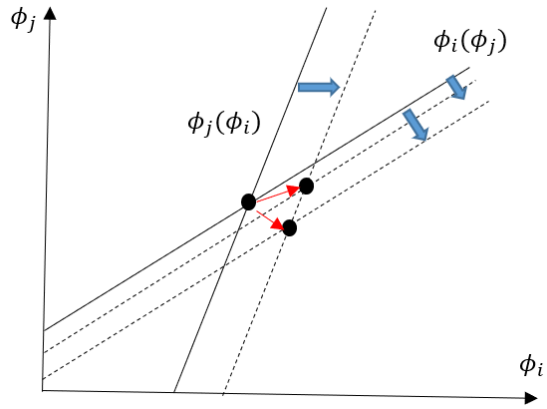
The denominator $\underbrace{\frac{\partial^2\pi_i}{\partial{\phi_i}^2}}_{<0}\underbrace{\frac{\partial^2\pi_j}{\partial{\phi_j}^2}}_{<0}-\underbrace{\frac{\partial^2\pi_i}{\partial\phi_i\partial\phi_j}}_{>0}\underbrace{\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}}_{>0}$ is positive, as $\left|\frac{\partial^2\pi_i}{\partial{\phi_i}^2}\right|>|\frac{\partial^2\pi_i}{\partial\phi_i\partial\phi_j}|$ and $|\frac{\partial^2\pi_j}{\partial{\phi_j}^2}|>|\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}|$. The numerator $-(\underbrace{\frac{\partial^2\pi_j}{\partial{\phi_j}^2}}_{<0}\underbrace{\frac{\partial^2\pi_i}{\partial\phi_i\partial I_i^a}}_{>0})+\underbrace{\frac{\partial^2\pi_i}{\partial\phi_i\partial\phi_j}}_{>0}\underbrace{\frac{\partial^2\pi_j}{\partial\phi_j\partial I_i^a}}_{<0}$ is also positive, as $\left|\frac{\partial^2\pi_j}{\partial{\phi_j}^2}\right|>|\frac{\partial^2\pi_i}{\partial\phi_i\partial\phi_j}|$ and $|\frac{\partial^2\pi_i}{\partial\phi_i\partial I_i^a}>\frac{\partial^2\pi_j}{\partial\phi_j\partial I_i^a}|$. Therefore $\frac{\partial\bar{\phi}_i}{\partial I_i^a}>0$.

Solving $\frac{\partial\bar{\phi}_j}{\partial I_i^a}$ as follows:

$$\frac{\partial\bar{\phi}_j}{\partial I_i^a}=\frac{\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}\frac{\partial^2\pi_i}{\partial\phi_i\partial I_i^a}-\frac{\partial^2\pi_i}{\partial{\phi_i}^2}\frac{\partial^2\pi_j}{\partial\phi_j\partial I_i^a}}{\frac{\partial^2\pi_i}{\partial{\phi_i}^2}\frac{\partial^2\pi_j}{\partial{\phi_j}^2}-\frac{\partial^2\pi_i}{\partial\phi_i\partial\phi_j}\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}}$$

The denominator of $\frac{\partial\bar{\phi}_j}{\partial I_i^a}$ is the same as $\frac{\partial\bar{\phi}_i}{\partial I_i^a}$, which is positive. Numerator $\underbrace{\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}}_{>0}\underbrace{\frac{\partial^2\pi_i}{\partial\phi_i\partial I_i^a}}_{>0}-\underbrace{\frac{\partial^2\pi_i}{\partial{\phi_i}^2}}_{<0}\underbrace{\frac{\partial^2\pi_j}{\partial\phi_j\partial I_i^a}}_{<0}$ has uncertain sign, which depends on the relative magnitude of $\frac{\partial^2\pi_j}{\partial\phi_i\partial\phi_j}\frac{\partial^2\pi_i}{\partial\phi_i\partial I_i^a}$ and $\frac{\partial^2\pi_i}{\partial{\phi_i}^2}\frac{\partial^2\pi_j}{\partial\phi_j\partial I_i^a}$. As shown in following Figure A1, when I_i^a increases, the best response function $\phi_j(\phi_i)$ moves outward, and the best response function $\phi_i(\phi_j)$ moves downward. If $\phi_i(\phi_j)$ does not move too much with I_i^a, the new equilibrium concession fees increase for both ϕ_i and ϕ_j. If $\phi_i(\phi_j)$ moves more with I_i^a, the new equilibrium concession fee ϕ_i will still increase, but concession fee ϕ_j will decrease. With the functional form imposed in this study, we can derive that $\frac{\partial\bar{\phi}_j}{\partial I_i^a}<0$.

Figure A1 The impact of increased port authority adaptation I_i^a on the best response functions of competing port authorities' concession fee at operation stage



Analogously, we are able to prove $\frac{\partial \bar{\phi}_i}{\partial I_i^t} > 0$, and the sign $\frac{\partial \bar{\phi}_j}{\partial I_i^t}$ depends on the relative magnitude of $\frac{\partial^2 \pi_j}{\partial \phi_i \partial \phi_j} \frac{\partial^2 \pi_i}{\partial \phi_i \partial I_i^t}$ and $\frac{\partial^2 \pi_i}{\partial {\phi_i}^2} \frac{\partial^2 \pi_j}{\partial \phi_j \partial I_i^t}$. With our functional form, it can be derived that $\frac{\partial \bar{\phi}_j}{\partial I_i^t} < 0$.

Taking total derivatives of FOCs of monopoly port authority with respect to I_i^a:

$$\frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial \phi_i \partial I_i^a} + \frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial {\phi_i}^2} \frac{\partial \tilde{\phi}_i}{\partial I_i^a} + \frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial \phi_i \partial \phi_j} \frac{\partial \tilde{\phi}_j}{\partial I_i^a} = 0$$

$$\frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial \phi_j \partial I_i^a} + \frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial \phi_i \partial \phi_j} \frac{\partial \tilde{\phi}_i}{\partial I_i^a} + \frac{\partial^2(\pi_i(\tilde{\phi}_i,\tilde{\phi}_j)+\pi_j(\tilde{\phi}_i,\tilde{\phi}_j))}{\partial {\phi_j}^2} \frac{\partial \tilde{\phi}_j}{\partial I_i^a} = 0$$

Solving $\frac{\partial \tilde{\phi}_i}{\partial I_i^a}$,

$$\frac{\partial \tilde{\phi}_i}{\partial I_i^a} = \frac{-\left(\overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial \phi_j \partial I_i^a}}^{<0} \overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial \phi_i \partial \phi_j}}^{>0}\right) + \overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial \phi_i \partial I_i^a}}^{>0} \overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial {\phi_j}^2}}^{<0}}{\underbrace{\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial \phi_i \partial \phi_j}\right)^2 - \left(\frac{\partial^2(\pi_i+\pi_j)}{\partial {\phi_i}^2}\right)\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial {\phi_j}^2}\right)}_{<0}} > 0$$

The denominator $(\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j})^2-\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2}\right)\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_j}^2}\right)<0$, as suggested by the Hessian condition for monopoly port authority to maximize profit. For the numerator, $\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_j}^2}\right|>\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j}\right|$, and $\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial I_i^a}\right|>\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_j\,\partial I_i^a}\right|$, such that the numerator is positive as well.

Solving for $\frac{\partial\tilde{\phi}_i}{\partial I_j^a}$:

$$\frac{\partial\tilde{\phi}_i}{\partial I_j^a}=\frac{\overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_j\,\partial I_i^a}}^{<0}\overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2}}^{<0}-\overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j}}^{>0}\overbrace{\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial I_i^a}}^{>0}}{\underbrace{(\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j})^2-(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2})(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_j}^2})}_{<0}}$$

The denominator $(\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j})^2-\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2}\right)\left(\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_j}^2}\right)<0$. For numerator, $\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_j\,\partial I_i^a}\right|<\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial I_i^a}\right|$ and $\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2}\right|<\left|\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j}\right|$, thus the sign of the numerator is uncertain. We thus have to depend on our functional setup to determine the sign of $\frac{\partial\tilde{\phi}_i}{\partial I_j^a}$ with the result as $\frac{\partial\tilde{\phi}_i}{\partial I_j^a}=0$.

Analogously, it can be shown that $\frac{\partial\tilde{\phi}_i}{\partial I_i^t}>0$ and the sign of $\frac{\partial\tilde{\phi}_j}{\partial I_i^t}$ depends on the relative magnitude of $\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_j\,\partial I_i^a}\,\frac{\partial^2(\pi_i+\pi_j)}{\partial{\phi_i}^2}$ and $\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial\phi_j}\,\frac{\partial^2(\pi_i+\pi_j)}{\partial\phi_i\,\partial I_i^a}$. The signs of derivatives of $\tilde{p}_i(\bar{\phi}_i,\bar{\phi}_j,I)$; $\tilde{p}_j(\bar{\phi}_i,\bar{\phi}_j,I)$ and $\tilde{p}_i(\tilde{\phi}_i,\tilde{\phi}_i,I)$; $\tilde{p}_j(\tilde{\phi}_i,\tilde{\phi}_i,I)$ to I_i^a and I_i^t can only be judged with functional setup.

A2. Best response function of optimal adaptation investments

With competing port authorities, for port authority i, the best response function of its own adaptation investment I_i^a to I_i^t conditional on the other port's adaptation investment I_j^a and I_j^t is as:

$$I_i^a|I_j^a,I_j^t=\frac{0.33\eta\,[(V+0.50t)\Omega-D\Psi]-0.032\,\eta^2\Psi\left(I_j^a+I_j^t\right)}{\omega t-0.36\,\eta^2\Psi}+\frac{0.36\,\eta^2\Psi}{\omega t-0.36\,\eta^2\Psi}I_i^t=A+BI_i^t$$

where $A = \frac{0.33\eta\,[(V+0.5t)\Omega - D\Psi] - 0.032\,\eta^2\Psi\left(I_j^a + I_j^t\right)}{\omega t - 0.36\,\eta^2\Psi}$ and $B = \frac{0.36\,t\eta^2\Psi}{\omega t - 0.36\,\eta^2\Psi}$.

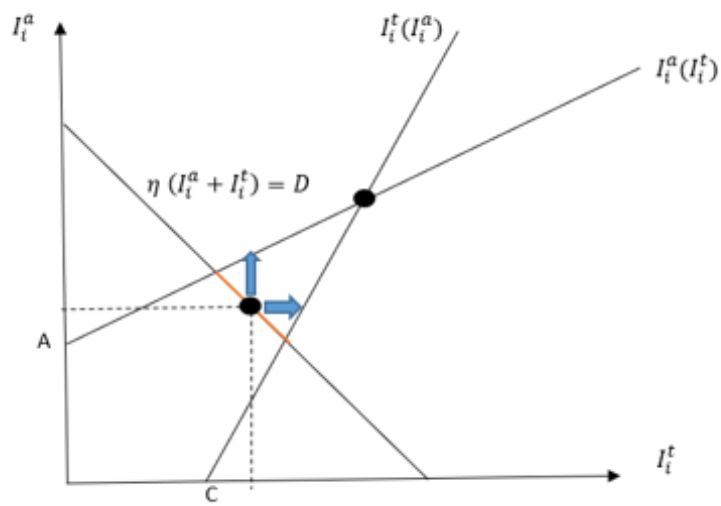
For terminal operator i, the best response function of its own adaptation investment in response to I_i^a is as:

$$I_i^t | I_j^a, I_j^t = \frac{0.16\eta\,[(V+0.5t)\Omega - D\Psi] - 0.015\,\eta^2\Psi\left(I_j^a + I_j^t\right)}{\omega t - 0.17\eta^2\Psi} + \frac{0.17\,\eta^2\Psi}{\omega t - 0.17\,\eta^2\Psi} I_i^a = C + F I_i^a$$

where $C = \frac{0.16\eta\,[(V+0.5t)\Omega - D\Psi] - 0.015\,\eta^2\Psi\left(I_j^a + I_j^t\right)}{\omega t - 0.17\eta^2\Psi}$ and $F = \frac{0.17\,\eta^2\Psi}{\omega t - 0.17\,\eta^2\Psi}$.

B and F are positive as the SOCs suggest $\omega > 0.36\,\frac{\eta^2}{t}\Psi$. The two best response functions are positively sloped, suggesting that the port adaptation investment at the same port is strategic complement. The best response functions are plotted as follows.

Figure A2 The best response adaptation investment functions for port authority and terminal operators at the same port



As shown in above figure, if $\omega < \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$, the binding constraint $\eta(I_i^a + I_i^t) = D$ indicated by the orange line cuts two best response lines inside of the interior Nash equilibrium. Any point

on the orange line is a Nash equilibrium, as port authority i and terminal operator i have the incentive to increase adaptation investment but already reaching constraint $\eta\ (I_i^a + I_i^t) = D$. Each party does not have incentive to deviate from its adaptation investment on the constraint. Thus, there are infinite Nash equilibria if the constraint $\eta\ (I_i^a + I_i^t) \leq D$ is binding.

For the port authority i, the best response function to the adaptation investment of the other port authority I_j^a, conditional on two ports' terminal operators' adaptation investments is as:

$$I_i^a | I_i^t, I_j^t = \frac{0.33\eta\ [(V+0.5t)\Omega - D\Psi] + 0.032\ \eta^2\Psi\left(11 I_i^a - I_j^t\right)}{\omega t - 0.36\ \eta^2\Psi} - \frac{0.032\ \eta^2\Psi}{\omega t - 0.36\ \eta^2\Psi} I_j^a = G + H I_j^a$$

where $G = \frac{0.33\eta\ [(V+0.5t)\Omega - D\Psi] + 0.032\ \eta^2\Psi\left(11 I_i^a - I_j^t\right)}{\omega t - 0.36\ \eta^2\Psi}$ and $H = -\frac{0.032\ \eta^2\Psi}{\omega t - 0.36\ \eta^2\Psi}$.

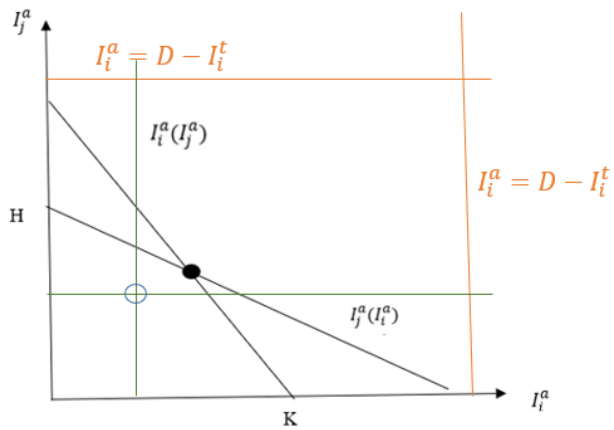
For the port authority j, the best response function to the adaptation investment of that of port authority i is as,

$$I_j^a | I_i^t, I_j^t = \frac{0.33\eta\ [(V+0.5t)\Omega - D\Psi] + 0.032\ \eta^2\Psi\left(11 I_j^a - I_i^t\right)}{\omega t - 0.36\ \eta^2\Psi} - \frac{0.032\ \eta^2\Psi}{\omega t - 0.36\ \eta^2\Psi} I_i^a = J + K I_j^a$$

where $J = \frac{0.33\eta\ [(V+0.5t)\Omega - D\Psi] + 0.032\ \eta^2\Psi\left(11 I_j^a - I_i^t\right)}{\omega t - 0.36\ \eta^2\Psi}$ and $K = -\frac{0.032\ \eta^2\Psi}{\omega t - 0.36\ \eta^2\Psi}$.

H and K are negative as SOCs suggest $\omega > 0.36\ \frac{\eta^2}{t}\Psi$. The two best response functions are negatively sloped, suggesting that the port authorities' adaptation investments at two different ports are strategic substitutes. In addition, the finite adaptation investment condition indicates that $\omega > 0.49\ \frac{\eta^2}{t}\Psi$. Therefore $|H| < 1$ and $|K| < 1$.

Figure A3 The best response adaptation investment functions for port authorities at two ports



A3. Expressions of equilibrium port adaptation investments and comparative statics

The expressions of $\frac{\partial \bar{I}_i^a}{\partial \Omega}$, $\frac{\partial \bar{I}_i^t}{\partial \Omega}$ and $\frac{\partial \bar{I}_i^a}{\partial \Sigma}$, $\frac{\partial \bar{I}_i^t}{\partial \Sigma}$ can be obtained as follows:

$$\frac{\partial \bar{I}_i^a}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right) - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial \bar{I}_i^t}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} - \left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right) - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial \bar{I}_i^a}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right) - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

$$\frac{\partial \bar{I}_i^t}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma} - \left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a\,2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right) - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

The expressions of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega}$, $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega}$ and $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma}$ can be solved as follows:

$$\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}-\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

$$\frac{\partial\, \tilde{I}_i^{\,t}}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma}-\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

The expressions of $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega}$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega}$ and $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma}$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma}$ can be obtained as follows:

$$\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega}-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega} = \frac{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega}}{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

$$\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma}-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)} \geq 0$$

$$\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma} = \frac{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma}-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma}}{\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}\right)-\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}+\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}\right)} \leq 0$$

Taking $\frac{\partial \bar{I}_i^{\,a}}{\partial \Omega}$ and $\frac{\partial \bar{I}_i^{\,a}}{\partial \Sigma}$ as example for the proof of $\frac{\partial \bar{I}_i^{\,a}}{\partial \Omega} \geq 0$, $\frac{\partial \bar{I}_i^{\,t}}{\partial \Omega} \geq 0$ and $\frac{\partial \bar{I}_i^{\,a}}{\partial \Sigma} \leq 0$, $\frac{\partial \bar{I}_i^{\,t}}{\partial \Sigma} \leq 0$.

$$\frac{\partial \bar{I}_i^{\,a}}{\partial \Omega} = \frac{\left(\overbrace{\overbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t}}^{\geq 0} + \overbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}}^{\leq 0}}^{\geq 0}\right)\overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}}^{\geq 0} - \left(\overbrace{\overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t^2}}}^{\leq 0} + \overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}}^{\leq 0}}^{\leq 0}\right)\overbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}}^{\geq 0}}{\underbrace{\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^{a^2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}}_{\leq 0}}_{\leq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t^2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}}_{\leq 0}}_{\leq 0}\right) - \left(\underbrace{\underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}}_{\geq 0}}_{\geq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t}}_{\geq 0} + \underbrace{\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}}_{\leq 0}}_{\geq 0}\right)}_{\geq 0}} \geq 0$$

For the denominator $\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^{a^2}} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right)\left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t^2}} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right) - \left(\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} + \frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right)\left(\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} + \frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right)$, the second-order derivatives suggest $\frac{\partial^2 E[\pi_i]}{\partial I_i^{a^2}} \leq 0$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a} \leq 0$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t^2}} \leq 0$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t} \leq 0$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a} \leq 0$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a} \geq 0$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t} \geq 0$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t} \leq 0$. $\left|\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^a}\right| = \left|\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_j^t}\right|$ and $\left|\frac{\partial^2 E[\pi_i]}{\partial I_i^{a^2}}\right| \geq \left|\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial I_i^t}\right|$, $\left|\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t^2}}\right| \geq \left|\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right|$ and $\left|\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}\right| = \left|\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}\right|$. Thus, it is concluded that the denominator is positive. The sign of $\frac{\partial \bar{I}_i^{\,a}}{\partial \Omega}$, therefore, depends on the sign of $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$.

The proof of $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} \geq 0$ is as follows. Substituting $\tilde{I}_i^{\,a} = \tilde{I}_j^{\,a} = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} = \frac{\eta[0.26\omega t^2 + [(0.12\psi - 0.24\Omega^2)\eta^2 + (0.5V - 0.99D\Omega)\omega]t + (0.48\Omega^2 - 0.24\psi)V\eta^2]}{1.60\omega t - 0.75\eta^2\psi}$. The denominator of $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega}$ is $1.60\omega t - 0.75\eta^2\psi > 0$. For the numerator, it is an increasing function inω. The finite adaptation investment condition requires $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} = \frac{0.16(2V+t)\eta}{t} > 0$. Therefore, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Omega} > 0$ when $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$.

Similarly, one can also show $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$. Substituting $\tilde{I}_i^{\,a} = I_j^a = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} = \frac{\eta\left[0.24(V+0.5t)\left(2\Omega^2 - \psi\right)\eta^2 + (0.5V + 0.25t - D\Omega)\omega t\right]}{3.2\omega t - 1.6\eta^2\psi}$, with the denominator $3.2\omega t - 1.6\eta^2\psi$ to be positive, and numerator as an increasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} = \frac{0.15(2V+t)\eta}{t} > 0$. Therefore, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} > 0$ when $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$.

Similarly, it can also been shown that the signs of $\frac{\partial \bar{I}_i^{\,a}}{\partial \Sigma}$ and $\frac{\partial \bar{I}_i^{\,t}}{\partial \Sigma}$ depend on $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$. The proof of $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma} \leq 0$ is as follows. Substituting $\tilde{I}_i^{\,a} = I_j^a = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma}$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma} = \frac{\eta[0.48(V+0.5t)\Omega\eta^2 - D\omega t]}{t(3.1\omega t - 1.5\psi\eta^2)}$. The denominator $t(3.1\omega t - 1.5\psi\eta^2)$ is positive, and the numerator is a decreasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma} = 0$. Therefore, $\frac{\partial^2 E[\pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$ when $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$.

Similarly, one can also show $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$. Substituting $\tilde{I}_i^{\,a} = I_j^a = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} = \frac{\eta[0.48(V+0.5t)\Omega\eta^2 - D\omega t]}{t(6.4\omega t - 3.1\psi\eta^2)}$. The denominator $t(6.4\omega t - 3.1\psi\eta^2)$ is positive, and the numerator is a decreasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} = 0$. Therefore, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$ when $\omega \geq \frac{0.48\,\Omega(V+0.5t)\eta^2}{Dt}$. Analogously, the sign of $\frac{\partial \bar{I}_i^{\,t}}{\partial \Sigma}$ also depends on $\frac{\partial^2 E[\pi_i]}{\partial I_i^a \partial \Sigma}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$, which is negative.

Taking $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega}$ and $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma}$ as an example for the proof of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} \geq 0$, $\frac{\partial \tilde{I}_i^{\,t}}{\partial \Omega} \geq 0$ and $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma} \leq 0$, $\frac{\partial \tilde{I}_i^{\,t}}{\partial \Sigma} \leq 0$.

$$\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega} = \frac{\left(\overbrace{\overbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}}^{\geq 0} + \overbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}}^{\leq 0}}^{\geq 0}\right)\overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}}^{\geq 0} - \left(\overbrace{\overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}}^{\leq 0} + \overbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}}^{\leq 0}}^{\leq 0}\right)\overbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}}^{\geq 0}}{\underbrace{\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^{a\,2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^a}}_{\leq 0}}_{\leq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^{t\,2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^t}}_{\leq 0}}_{\leq 0}\right) - \left(\underbrace{\underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_j^a}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial I_i^a}}_{\geq 0}}_{\geq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_i^t}}_{\geq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial I_j^t}}_{\leq 0}}_{\geq 0}\right)}_{\geq 0}} \geq 0$$

It can be shown that the sign of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Omega}$ depends on sign of $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$. The proof of $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega} \geq 0$ is as follows. Substituting $\tilde{I}_i^{\,a} = \tilde{I}_j^{\,a} = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega}$, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega} = \frac{\eta[0.25\mathrm{t}^2\omega + [(0.11\psi - 0.22\Omega^2)\eta^2 + (0.5V - D\Omega)\omega]t + 0.223(\Omega^2 - \psi)V\eta^2]}{t(1.67\omega t - 0.74\eta^2\psi)}$, with the denominator to be positive, and with numerator as an increasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega} = \frac{0.15(2V+t)\eta}{t}$. Therefore, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Omega} \geq 0$ when $\omega \geq \frac{044\,\Omega(V+0.5t)\eta^2}{Dt}$.

Similarly, one can show $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$. Substituting $\tilde{I}_i^{\,a} = I_j^{\,a} = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} = \frac{\eta[0.25\mathrm{t}^2\omega + [(0.11\psi - 0.22\Omega^2)\eta^2 + (0.5V - D\Omega)\omega]t + 0.223(\Omega^2 - \psi)V\eta^2]}{t(3.43\omega t - 1.53\eta^2\psi)}$, with the denominator to be positive, and the numerator as an increasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} = \frac{0.15(2V+t)\eta}{t}$. Therefore, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Omega} \geq 0$ when $\omega \geq \frac{044\,\Omega(V+0.5t)\eta^2}{Dt}$.

It can also been shown that the sign of $\frac{\partial \tilde{I}_i^{\,a}}{\partial \Sigma}$ and $\frac{\partial \tilde{I}_i^{\,t}}{\partial \Sigma}$ depends on $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma}$ and $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$. The proof of $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma} \leq 0$ is as follows. Substituting $\tilde{I}_i^{\,a} = \tilde{I}_j^{\,a} = \frac{\eta[(2V+t)\,\Omega - 2D\Psi]}{6.7\omega t - 3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega - 2D\Psi]}{14\omega t - 6.\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma}$, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma} = \frac{\eta[0.446(V+0.5t)\Omega\eta^2 - D\omega t]}{t(3.33\omega t - 1.49\psi\eta^2)}$, with the denominator to be positive, and the numerator as a decreasing function in ω. The finite adaptation investment condition requires $\omega \geq$

$\frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i+\pi_j]}{\partial I_i^a \partial \Sigma} = 0$. Therefore, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$ when $\omega \geq \frac{044\,\Omega(V+0.5t)\eta^2}{Dt}$.

Similarly, one can also show $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$. Substituting $\tilde{I}_i^{\,a} = \tilde{I}_j^{\,a} = \frac{\eta[(2V+t)\,\Omega-2D\Psi]}{6.7\omega t-3\Psi\eta^2}$, $\tilde{I}_i^{\,t} = \tilde{I}_j^{\,t} = \frac{\eta[(2V+t)\Omega-2D\Psi]}{14\omega t-6.\Psi\eta^2}$ into $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma}$. $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} = \frac{\eta[0.446(V+0.5t)\Omega\eta^2-D\omega t]}{t(6.86\omega t-3.06\psi\eta^2)}$, with the denominator to be positive, and the numerator as a decreasing function in ω. The finite adaptation investmentcondition requires $\omega \geq \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.44\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} = 0$. Therefore, $\frac{\partial^2 E[\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$ when $\omega \geq \frac{044\,\Omega(V+0.5t)\eta^2}{Dt}$.

Taking $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega}$ and $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma}$ as example for the proof of $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} \geq 0$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Omega} \geq 0$ and $\frac{\partial \hat{I}_i^{\,a}}{\partial \Sigma} \leq 0$, $\frac{\partial \hat{I}_i^{\,t}}{\partial \Sigma} \leq 0$.

$$\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega} = \frac{\overbrace{\left(\overbrace{\overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}}^{\geq 0} + \overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}}^{\leq 0}}^{\geq 0}\right)\overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega}}^{\geq 0} - \left(\overbrace{\overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}}^{\leq 0} + \overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}}^{\leq 0}}^{\leq 0}\right)\overbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}}^{\geq 0}}^{\geq 0}}{\underbrace{\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{a\,2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^a}}_{\leq 0}}_{\leq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^{t\,2}}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^t}}_{\leq 0}}_{\leq 0}\right) - \left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_j^a}}_{\leq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial I_i^a}}_{\geq 0}}_{\geq 0}\right)\left(\underbrace{\underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_i^t}}_{\geq 0} + \underbrace{\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial I_j^t}}_{\leq 0}}_{\geq 0}\right)}_{\geq 0}} \geq 0$$

It can be shown that the sign of $\frac{\partial \hat{I}_i^{\,a}}{\partial \Omega}$ depends on the sign of $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}$ and $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega}$. The proof of $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} \geq 0$ is as follows. Substituting $\hat{I}_i^{\,a} = \hat{I}_j^{\,a} = \hat{I}_i^{\,t} = \hat{I}_j^{\,t} = \frac{\eta\,[(2V+t)\,\Omega-2D\Psi]}{4.1\,\omega t-4\,\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} = \frac{\eta[0.25\mathrm{t}^2\omega+[(0.48\Omega^2-0.24\psi)\eta^2+(0.5V-D\Omega)\omega]t+0.48(2\Omega^2-\psi)V\eta^2]}{t(\omega t-\eta^2\psi)}$, with the denominator to be positive, and the numerator to be an increasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.97\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} = \frac{0.24(2V+t)\eta}{t}$. Therefore $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} \geq 0$ when $\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$. In addition, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Omega} = \frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Omega} \geq 0$.

It can also been shown that the sign of $\frac{\partial \hat{I}_i^a}{\partial \Sigma}$ and $\frac{\partial \hat{I}_i^t}{\partial \Sigma}$ depends on the sign of $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma}$ and $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma}$.

The proof of $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} \leq 0$ is as follows. Substituting $\hat{I}_i^a = \hat{I}_j^a = \hat{I}_i^t = \hat{I}_j^t = \frac{\eta\,[(2V+t)\,\Omega-2D\Psi]}{4.1\,\omega t-4\,\Psi\eta^2}$ into $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} = \frac{\eta[0.97(V+0.5t)\Omega\eta^2-D\omega t]}{t(2.1\omega t-2\psi\eta^2)}$, with the denominator to be positive, and the numerator to be a decreasing function in ω. The finite adaptation investment condition requires $\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$. When $\omega = \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} = 0$. Therefore $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} \leq 0$ when $\omega \geq \frac{0.97\,\Omega(V+0.5t)\eta^2}{Dt}$. In addition, $\frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^a \partial \Sigma} = \frac{\partial^2 E[\pi_i+\Pi_i]}{\partial I_i^t \partial \Sigma} \leq 0$.

A4. The Effects of Port Competition Intensity on equilibrium adaptation

The new equilibrium adaptation with competing port authorities is obtained as follows:

$$\bar{I}_i^a(t') = \bar{I}_j^a(t')$$
$$= \frac{\eta(4t'+t)(4t'+3t)(2t'+t)(128t'^4+256t'^3t+156t'^tt^2+28t't^3+t^4)[(2V+t)\,\Omega-2D\Psi]}{(4t'+3t)(4t'+t)^2\left(16t'^2+18t't+3t^2\right)\left(16t'^2+14t't+t^2\right)^2\omega t-8\left(6t'^2+6t't+t^2\right)(8t'^2+8t't+t^2)(2t'+t)(128t'^4+256t'^3t+156t'^tt^2+28t't^3+t^4)\Psi\eta^2}$$

$$\bar{I}_i^t(t') = \bar{I}_j^t(t')$$
$$= \frac{\eta(2t'+t)\left(8t'^2+8t't+t^2\right)^2(128t'^4+256t'^3t+156t'^tt^2+28t't^3+t^4)[(2V+t)\,\Omega-2D\Psi]}{(4t'+3t)(4t'+t)^2\left(16t'^2+18t't+3t^2\right)\left(16t'^2+14t't+t^2\right)^2\omega t-8\left(6t'^2+6t't+t^2\right)(8t'^2+8t't+t^2)(2t'+t)(128t'^4+256t'^3t+156t'^tt^2+28t't^3+t^4)\Psi\eta^2}$$

The equilibrium adaptation with monopoly port authority is obtained as follows:

$$\tilde{I}_i^a(t') = \tilde{I}_j^a(t') = \frac{0.25\eta(4t'+3t)(2t'+t)(4t'+t)[(2V+t)\,\Omega-2D\Psi]}{(4t'+3t)(4t'+t)^2\omega t-(6t'^2+6t't+t^2)(2t'+t)\Psi\eta^2}$$

$$\tilde{I}_i^t(t') = \tilde{I}_j^t(t') = \frac{0.25\eta(2t'+t)(8t'^2+8t't+t^2)[(2V+t)\,\Omega-2D\Psi]}{(4t'+3t)(4t'+t)^2\omega t-(6t'^2+6t't+t^2)(2t'+t)\Psi\eta^2}$$

In addition, the equilibrium adaptation with competing port authorities but allowing intra-port coordination is solved as follows:

$$\hat{I}_i^{\,a}(t') = \hat{I}_j^{\,a}(t') = \hat{I}_i^{\,t}(t') = \hat{I}_j^{\,t}(t')$$

$$= \frac{\begin{bmatrix} 4\eta(2t'+t)\left(6t'^2+6t't+3t^2\right)\left(8t'^2+8t't+3t^2\right)\left(128t'^4+256t'^3t+156t'^t t^2+28t't^3+t^4\right) \\ [(2V+t)\,\Omega - 2D\Psi] \end{bmatrix}}{\begin{bmatrix} (4t'+3t)(4t'+t)^2\left(16t'^2+18t't+3t^2\right)\left(16t'^2+14t't+t^2\right)^2\omega t - \\ 16\left(6t'^2+6t't+t^2\right)\left(8t'^2+8t't+t^2\right)(2t'+t) \\ \left(128t'^4+256t'^3t+156t'^t t^2+28t't^3+t^4\right)\Psi\eta^2 \end{bmatrix}}$$

Appendix B: Appendix for Chapter 3

B1. Proof of Proposition 3.1

By imposing symmetry and totally differentiating FOC (Eq. (3.7)) with respect to $\bar{s}_H$, we obtain Eq. (B.1).

$$\left(\frac{\partial P_A}{\partial \bar{s}_H} + \frac{\partial P_A}{\partial q_A}\frac{\partial q_A^*}{\partial \bar{s}_H}\right) + \frac{1}{N}\frac{\partial q_A^*}{\partial \bar{s}_H}\frac{\partial P_A}{\partial q_A} + \frac{q_A}{N}\left(\frac{\partial^2 P_A}{\partial q_A^2}\frac{\partial q_A^*}{\partial \bar{s}_H} + \frac{\partial^2 P_A}{\partial q_A \partial \bar{s}_H}\right) = 0 \tag{B.1}$$

Rearrange Eq. (B.1), we have Eq. (3.8).

The second-order condition (SOC) with respect to q_j^A must hold for the existence of optimal airline quantity. Thus, we have:

$$2\frac{\partial P_A}{\partial q_A} + q_j^A \frac{\partial^2 P_A}{\partial {q_A}^2} < 0 \tag{B.2}$$

When $N = 1$, the denominator of Eq. (3.8) is exactly Eq. (B.2). When $N > 1$ and the demand is linear (i.e., $\frac{\partial^2 P_A}{\partial q_A^2} = 0$), the denominator of Eq. (3.8) is also negative. In addition, when the carriers' decision variables are strategic substitutes (Bulow et al., 1985; Zhang and Zhang, 2010; Lin and Zhang, 2017), the denominator of Eq. (3.8) is again negative.

The FOC of airline competition can be re-written as follows:

$$(P_A - c)\frac{\partial q_A(P_A, \bar{s}_H)}{\partial P_A} + \frac{q_A}{N}(P_A, \bar{s}_H) = 0 \tag{B.3}$$

Totally differentiate Eq. (B.3) with respect to $\bar{s}_H$, we have:

$$\frac{\partial P_A^*}{\partial s_H}\frac{\partial q_A}{\partial P_A} + (P_A - c)\left(\frac{\partial^2 q_A}{\partial {P_A}^2}\frac{\partial P_A^*}{\partial s_H} + \frac{\partial^2 q_A}{\partial P_A \partial s_H}\right) + \frac{1}{N}\frac{\partial q_A}{\partial P_A}\frac{\partial P_A^*}{\partial s_H} + \frac{1}{N}\frac{\partial q_A}{\partial s_H} = 0 \tag{B.4}$$

Rearrange Eq. (B.4), we have Eq. (3.9). Substituting $-\frac{\partial q_A}{\partial P_A}(P_A - c)$ for q_j^A in Eq. (B.2) from the FOC, and then multiplying both sides of Eq. (B.2) by $(\frac{\partial q_A}{\partial P_A})^2$, we have $2\frac{\partial q_A}{\partial P_A} - \frac{\partial^2 P_A}{\partial {q_A}^2}(\frac{\partial q_A}{\partial P_A})^3(P_A - c) < 0$. Since $\frac{\partial^2 q_A}{\partial {P_A}^2} = -\frac{\partial^2 P_A}{\partial {q_A}^2}(\frac{\partial q_A}{\partial P_A})^3$ by implicit function theorem,[87] the following inequality holds.

$$2\frac{\partial q_A}{\partial P_A} + (P_A - c)\frac{\partial^2 q_A}{\partial {P_A}^2} < 0 \tag{B.5}$$

When $N = 1$, the denominator of Eq. (3.9) is exactly Eq. (B.5). When $N > 1$ and the demand is linear (i.e., $\frac{\partial^2 P_A}{\partial q_A^2} = 0$), the denominator of Eq. (3.9) is also negative.

B2. Proof of Proposition 3.2

We prove Proposition 3.2 using more general functional forms. Assume the sensitivity of price to demand is not a function of HSR speed. That is $\partial(\frac{\partial P_A(q_A,\bar{s}_H)}{\partial q_A})/\partial \bar{s}_H = 0$. We have $\frac{dq_A^*}{d\bar{s}_H} = -\frac{N\frac{\partial P_A}{\partial \bar{s}_H}}{(N+1)\frac{\partial P_A}{\partial q_A}}$ and $\frac{dP_A^*}{d\bar{s}_H} = \frac{\partial P_A}{\partial q_A}\frac{dq_A^*}{d\bar{s}_H} + \frac{\partial P_A}{\partial \bar{s}_H} = \frac{\frac{\partial P_A}{\partial \bar{s}_H}}{N+1}$. Thus,

$$\frac{\frac{dq_A^*}{d\bar{s}_H}}{\frac{dP_A^*}{d\bar{s}_H}\frac{\partial q_A}{\partial P_A}} = -N \tag{B.6}$$

[87] Since P_A is a function of q_A and vice versa, i.e., $P_A = f(q_A)$ and $q_A = f^{-1}(P_A)$, we have $1 = \frac{\partial f(q_A)}{\partial q_A}\frac{\partial q_A}{\partial P_A}$. Differentiating both sides with respect to P_A gives $0 = \frac{\partial^2 f(q_A)}{\partial {q_A}^2}(\frac{\partial q_A}{\partial P_A})^2 + \frac{\partial f(q_A)}{\partial q_A}\frac{\partial^2 q_A}{\partial {P_A}^2}$. Thus, $\frac{\partial^2 q_A}{\partial {P_A}^2} = -\frac{\frac{\partial^2 f(q_A)}{\partial {q_A}^2}\left(\frac{\partial q_A}{\partial P_A}\right)^2}{\frac{\partial f(q_A)}{\partial q_A}} = -\frac{\frac{\partial^2 P_A}{\partial {q_A}^2}\left(\frac{\partial q_A}{\partial P_A}\right)^2}{\frac{\partial P_A}{\partial q_A}} = -\frac{\partial^2 P_A}{\partial {q_A}^2}\left(\frac{\partial q_A}{\partial P_A}\right)^3$.

A well-known result from Cournot competition:

$$\varepsilon_{q_A^*,P_A^*} = -\frac{1}{N}\frac{P_A^*}{P_A^* - c} \tag{B.7}$$

Since $\frac{dq_A^*}{d\bar{s}_H} = \frac{\partial q_A}{\partial P_A}\frac{dP_A^*}{d\bar{s}_H} + \frac{\partial q_A}{\partial \bar{s}_H}$, we divide both sides by $\frac{dP_A^*}{d\bar{s}_H}$ and multiply both sides by $\frac{P_A^*}{q_A^*}$. We obtain:

$$\frac{\varepsilon_{q_A^*,\bar{s}_H}}{\varepsilon_{P_A^*,\bar{s}_H}} = \frac{\frac{dq_A^*}{d\bar{s}_H}\frac{\bar{s}_H}{q_A^*}}{\frac{dP_A^*}{d\bar{s}_H}\frac{\bar{s}_H}{P_A^*}} = \left(\frac{\partial q_A}{\partial P_A} + \frac{\frac{\partial q_A}{\partial \bar{s}_H}}{\frac{dP_A^*}{d\bar{s}_H}}\right)\frac{P_A^*}{q_A^*} = \frac{\partial q_A}{\partial P_A}\frac{P_A^*}{q_A^*}\left(1 + \frac{\frac{\partial q_A}{\partial \bar{s}_H}}{\frac{dP_A^*}{d\bar{s}_H}\frac{\partial q_A}{\partial P_A}}\right) = \varepsilon_{q_A^*,P_A^*}\frac{\frac{dq_A^*}{d\bar{s}_H}}{\frac{dP_A^*}{d\bar{s}_H}\frac{\partial q_A}{\partial P_A}} = \frac{P_A^*}{P_A^* - c}$$

$$> 1$$

The last equality is by Eq. (B.6) and Eq. (B.7). Thus, the magnitude of $\varepsilon_{q_A^*,\bar{s}_H}$ must be larger than the magnitude of $\varepsilon_{P_A^*,\bar{s}_H}$.

B3. Proof of Proposition 3.3

From Eq. (3.18.1) and Eq. (3.18.2), we have:

$$\frac{\partial\left|\varepsilon_{q_A^*,s_H}\right|}{\partial\gamma} - \frac{\partial\left|\varepsilon_{P_A^*,s_H}\right|}{\partial\gamma}$$
$$= \frac{c\bar{s}_H(1+N)\left|\frac{\partial\mathcal{T}}{\partial\bar{s}_H} + \frac{\partial\mathcal{S}}{\partial\bar{s}_H}\right|(-c^2N + c\alpha_A(N-1) + \alpha_A^2 - \gamma^2(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))^2)}{(\alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})) - c)^2(Nc + \alpha_A - \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})))^2} \tag{B.8}$$

Since $\alpha_A - P_A > \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))$ due to the positive demand in Eq. (3.11.1), we have $\alpha_A - c > \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))$. Since $\gamma(\alpha_A - P_A) < \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))$ due to the positive demand in Eq. (3.11.2), we have $\gamma^2\big(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})\big) < \gamma(\alpha_A - P_A) < \alpha_H - P_H - (\mathcal{T}+\mathcal{S})$. Since $0 < \gamma < 1$, we have $\big(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})\big) > 0$.

The sign of $\frac{\partial\left|\varepsilon_{q_A^*,s_H}\right|}{\partial\gamma} - \frac{\partial\left|\varepsilon_{P_A^*,s_H}\right|}{\partial\gamma}$ is determined by the term $-c^2N + c\alpha_A(N-1) + \alpha_A^2 - \gamma^2(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))^2$. We have the following relation:

$$
\begin{aligned}
-c^2N + c\alpha_A(N-1) + \alpha_A^2 - \gamma^2\big(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})\big)^2 \\
&> -c^2N + c\alpha_A(N-1) + c(\alpha_A + \gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S}))) \\
&> c\left(N(\alpha_A - c) + \gamma\big(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})\big)\right) \\
&= c(N+1)\gamma(\alpha_H - P_H - (\mathcal{T}+\mathcal{S})) > 0
\end{aligned}
\tag{B.9}
$$

Table B1 Estimation results for airline traffic equation with assumed functional forms of $f(s_{it}) = s_{it}, s_{it}^2$, or $\sqrt{s_{it}}$ with subsamples based on HSR total travel time (including access and egress time between HSR stations and city centers)

Airline Traffic	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours
	$f(s_{it}) = s_{it}$			$f(s_{it}) = s_{it}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
α_1	-0.0027***	-0.0041***	-0.0182	-4.01×10^{-6}***	-6.28$\times 10^{-6}$***	3.39×10^{-6}	-0.081**	-0.157***	-0.0721
	(0.0010)	(0.0009)	(0.044)	(1.89×10^{-6})	(1.62$\times 10^{-6}$)	(1.19×10^{-5})	(0.026)	(0.021)	(0.735)
α_2	-0.137	-0.119	-0.104	-0.136	-0.119	-0.054	-0.137	-0.144*	-0.115
	(0.110)	(0.074)	(0.095)	(0.110)	(0.074)	(0.095)	(0.109)	(0.074)	(0.095)
HHI	-0.0824*	-0.081*	-0.0883**	-0.081*	-0.081*	-0.088**	-0.083*	-0.082**	-0.088**
	(0.044)	(0.042)	(0.043)	(0.044)	(0.043)	(0.043)	(0.044)	(0.042)	(0.043)
Population	-0.585	-0.777	-0.542	-0.605	-0.884	-0.491	-0.549	-0.636	-.488
	(0.656)	(0.632)	(0.684)	(0.657)	(0.635)	(0.683)	(0.655)	(0.630)	(0.682)
Income	-0.332**	-0.367***	-0.298	-0.329***	-0.372***	-0.298**	-0.334***	-0.357***	-0.297**
	(0.128)	(0.122)	(0.124)	(0.128)	(0.123)	(0.124)	(0.128)	(0.122)	(0.124)
LCC	-0.021	-0.020	-0.020	-0.021	-0.021	-0.020	-0.021	-0.020	-0.020
	(0.062)	(0.061)	(0.060)	(0.062)	(0.061)	(0.060)	(0.062)	(0.061)	(0.060)
Tourism	0.015	0.028	0.045	0.0114	0.016	0.053*	0.012	0.035	0.056
	(0.048)	(0.041)	(0.044)	(0.048)	(0.041)	(0.048)	(0.047)	(0.041)	(0.049)
Spring	-0.171***	-0.182***	-0.219***	-0.171***	0.752***	-0.219***	-0.229***	-0.236***	-0.218***
	(0.045)	(0.043)	(0.042)	(0.045)	(0.235)	(0.042)	(0.043)	(0.042)	(0.042)
Summer	0.232	0.230	0.234	0.233	0.229	0.234	0.231	0.230	0.234
	(0.161)	(0.158)	(0.155)	(0.161)	(0.159)	(0.155)	(0.161)	(0.157)	(0.155)
Autumn	-0.571***	-0.578***	-0.626	-0.571***	0.358**	-0.626**	-0.629***	-0.633***	-0.626***
	(0.161)	(0.158)	(0.153)	(0.161)	(0.161)	(0.153)	(0.158)	(0.155)	(0.153)
Year2011	0.148***	0.152***	-0.208	0.148***	1.093***	-0.209***	0.759***	0.762***	0.756***
	(0.029)	(0.028)	(0.157)	(0.029)	(0.233)	(0.157)	(0.158)	(0.155)	(0.153)
Year2012	0.854***	0.865***	0.848***	0.854***	0.869***	0.846***	0.853***	0.858***	0.846***
	(0.160)	(0.157)	(0.154)	(0.160)	(0.157)	(0.154)	(0.159)	(0.156)	(0.154)
Year2013	-0.038	-0.028	-0.104	-0.038***	0.913***	-0.106***	-0.096***	-0.092***	-0.106***
	(0.166)	(0.163)	(0.158)	(0.166)	(0.161)	(0.158)	(0.163)	(0.160)	(0.158)

Airline Traffic	**All**	**< 5 hours**	**> 5 hours**	**All**	**< 5 hours**	**> 5 hours**	**All**	**< 5 hours**	**> 5 hours**
	$f(s_{it}) = s_{it}$			$f(s_{it}) = {s_{it}}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
Constant	18.842***	20.460***	18.723***	18.912***	20.179***	18.028***	18.902***	20.170***	18.310***
	(4.177)	(4.014)	(4.514)	(4.187)	(4.033)	(4.349)	(4.171)	(4.002)	(4.328)
Time trend fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
HSR route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Observations	1,036	966	980	1,036	966	980	1,036	966	980

Note:

1. The treated routes included in <5 hours total HSR travel time (including access and egress time between HSR stations and city center) subsample are Shanghai-Hefei, Beijing-Taiyuan, Guangzhou-Changsha, Guangzhou-Wuhan. The treated routes included in > 5 hours subsample are Shanghai-Zhengzhou, Shanghai-Fuzhou, Shanghai-Wuhan, Shanghai-Xiamen, Guangzhou-Hefei.
2. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_{\mathrm{i}}$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
3. ***<0.01, **<0.05, *<0.10.
4. Standard errors are in parentheses.

Table B2 Estimation results for airline price equation with assumed functional forms of $f(s_{it}) = s_{it}, s_{it}^2$, or $\sqrt{s_{it}}$ with subsamples based on HSR total travel time (including access and egress time between HSR stations and city centers)

Airline price	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours
	$f(s_{it}) = s_{it}$			$f(s_{it}) = s_{it}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
β_1	-0.0015**	-0.0016***	-0.013	-3.01×10^{-6}***	-3.12$\times 10^{-6}$***	-1.29×10^{-7}	-0.0368***	-0.066***	0.070
	(0.0004)	(0.0003)	(0.018)	(7.73$\times 10^{-7}$)	(6.61$\times 10^{-7}$)	(4.99$\times 10^{-6}$)	(0.0009)	(0.011)	(0.726)
β_2	-0.052	-0.023	0.0004	-0.051	-0.023	0.046	-0.012	-0.051	0.0012
	(0.045)	(0.030)	(0.040)	(0.045)	(0.030)	(0.040)	(0.030)	(0.045)	(0.040)
HHI	0.109***	0.104***	0.109***	0.110***	0.104***	0.109***	0.103***	0.109***	0.109***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)
Population	0.605**	0.626***	0.906***	0.584**	0.572**	0.922***	0.671***	0.625**	0.927***
	(0.268)	(0.258)	(0.286)	(0.268)	(0.258)	(0.285)	(0.259)	(0.269)	(0.285)
Income	0.110**	0.100**	0.096*	0.110**	0.096*	0.095*	0.104**	0.112**	0.095*
	(0.052)	(0.050)	(0.051)	(0.052)	(0.050)	(0.051)	(0.050)	(0.052)	(0.051)
LCC	0.0045	0.0038	0.004	0.004	0.0038	0.004	0.003	0.004	0.004
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Tourism	-0.0004	0.005	0.003	0.003	0.003	0.002	0.004	-0.005	0.003
	(0.019)	(0.016)	(0.018)	(0.019)	(0.016)	(0.020)	(0.017)	(0.019)	(0.020)
Spring	0.021	0.018	-0.032*	0.021***	0.438***	-0.032**	-0.031*	-0.030*	-0.0320*
	(0.018)	(0.017)	(0.017)	(0.018)	(0.095)	(0.017)	(0.017)	(0.018)	(0.017)
Summer	0.187***	0.183***	0.184***	0.188***	0.183***	0.184***	0.183***	0.187***	0.184**
	(0.066)	(0.064)	(0.065)	(0.065)	(0.064)	(0.065)	(0.064)	(0.066)	(0.065)
Autumn	-0.149**	-0.151**	-0.199**	-0.150**	0.269***	-0.199***	-0.202***	-0.201***	-0.199***
	(0.066)	(0.064)	(0.064)	(0.066)	(0.065)	(0.064)	(0.063)	(0.065)	(0.064)
Year2011	0.012	0.012	-0.204***	0.012	0.435***	-0.204***	0.289***	0.290***	0.284***
	(0.012)	(0.011)	(0.065)	(0.012)	(0.094)	(0.065)	(0.063)	(0.065)	(0.064)
Year2012	0.247***	0.248***	0.239***	0.248***	0.250***	0.238***	0.246***	0.247***	0.238***

Airline price	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours	All	< 5 hours	> 5 hours
	$f(s_{it}) = s_{it}$			$f(s_{it}) = {s_{it}}^2$			$f(s_{it}) = \sqrt{s_{it}}$		
	(0.065)	(0.064)	(0.064)	(0.065)	(0.064)	(0.064)	(0.064)	(0.065)	(0.064)
Year2013	-0.256***	-0.252***	-0.312***	-0.255***	0.171***	-0.312***	-0.306***	-0.308***	-0.313***
	(0.068)	(0.066)	(0.066)	(0.068)	(0.065)	(0.066)	(0.065)	(0.067)	(0.066)
Constant	-6.051***	-6.031***	-7.638***	-5.926***	-6.101***	-7.975***	-6.110***	-6.046***	-8.041***
	(1.711)	(1.642)	(1.888)	(1.711)	(1.642)	(1.819)	(1.645)	(1.713)	(1.811)
Time trend fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
HSR route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Observations	1,036	966	980	1,036	966	980	1,036	966	980

Note:

1. The treated routes included in <5 hours total HSR travel time (including access and egress time between HSR stations and city center) subsample are Shanghai-Hefei, Beijing-Taiyuan, Guangzhou-Changsha, Guangzhou-Wuhan. The treated routes included in > 5 hours subsample are Shanghai-Zhengzhou, Shanghai-Fuzhou, Shanghai-Wuhan, Shanghai-Xiamen, Guangzhou-Hefei.
2. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_i$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
3. ***<0.01, **<0.05, *<0.10.
4. Standard errors are in parentheses

Table B3 The estimated HSR speed effect with assumed functional forms of $f(s_{it}) = s_{it}$, s_{it}^2 , or $\sqrt{s_{it}}$

(a) For 250 km/hr HSR lines

		< 5 hours		
$f(s_{it})$		s_{it}	s_{it}^2	$\sqrt{s_{it}}$
Elasticity to HSR speed	$\varepsilon_{q_A^*,s_H}$	-1.03	-0.79	-1.24
	$\varepsilon_{p_A^*,s_H}$	-0.40	-0.39	-0.52
Impact of HSR speed reduction	Traffic Change %	-20.5%	-15.7 %	-24.8%
	Price Change %	-8%	-7.8%	-10.3%
Impact of HSR entry	Traffic Change %	-64%	-32%	-92%
	Price Change %	33%	-18%	-65%

Note: For total HSR travel time> 5 hours, the HSR speed effects are not calculated, because the estimated coefficients of $f(s_{it})$ are statistically insignificant.

(b) For 350 km/hr HSR lines

		< 5 hours		
$f(s_{it})$		s_{it}	s_{it}^2	$\sqrt{s_{it}}$
Elasticity to HSR speed	$\varepsilon_{q_A^*,s_H}$	-1.44	-1.54	-1.47
	$\varepsilon_{p_A^*,s_H}$	-0.57	-0.76	-0.62
Impact of HSR speed reduction	Traffic Change %	20%	22%	21%
	Price Change %	8 %	11 %	9 %
Impact of HSR entry	Traffic Change%	-76%	-54%	-95%
	Price Change %	-43%	-32%	-71%

Note: For total HSR travel time> 5 hours, the HSR speed effects are not calculated because the estimated coefficients of $f(s_{it})$ are statistically insignificant.

B4. Airline demand and price equation estimation

The airline demand equation can be regarded as a function of airline price P_{it}. The coefficient ρ_1 is the impact of HSR speed on airline demand conditional on the airline price. This is a measurement of direct HSR speed effect on passengers' utility. For airline price equation, it is from the supply side which is a function of airline demand. Speed effect variable is not included in the airline price equation because the HSR speed only has a direct effect on airline demand, and its impact on airline price has been controlled by the airline traffic variable in the price equation (referring to Eq. (3.7) of the theoretical model).

$$\begin{aligned}
\ln q_{it} = \rho_0 + \rho_1 \times f(s_{it}) \times HSR_{it} + \rho_2 \frac{1}{Post_accident_{it}} \times HSR_{it} + \rho_3 \ln P_{it} \\
+ \rho_4 \ln Dist_Air_i + \rho_5 \ln Pop_{it} + \rho_6 \ln Income_{it} + \rho_7 LCC_{it} \\
+ \rho_8 Tourism_i + \rho_9 Spring_t + \rho_{10} Summer_t + \rho_{11} Autumn_t \\
+ \rho_{12} Year_t + \rho_{13} HSR_{it} + \chi_i + \varpi_{it} \qquad \text{(B.10)} \\
\ln P_{it} = \eta_0 + \eta_1 \ln q_{it} + \eta_2 \ln Dist_Air_i + \eta_3 \ln HHI_{it} + \eta_4 \ln Pop_{it} + \eta_5 lnIncome_{it} \\
+ \eta_6 LCC_{it} + \eta_7 Tourism_i + \eta_8 Spring_t + \eta_9 Summer_t \\
+ \eta_{10} Autumn_t + \eta_{11} Year_t + \eta_{12} HSR_{it} + \varsigma_i + o_{it}
\end{aligned}$$

The GMM estimation results of the above system of equations are summarized in Table B4 and B5. First, the estimated coefficients for the HSR speed variable $f(s_{it})$ in the airline demand function are larger than those in the airline traffic equation. This is because HSR speed reduction can also cause airline price to rise, thus have a negative moderation on the airline traffic in the reduced-form airline traffic equation, which lowers the HSR speed effect on airline traffic. Second, the airline demand elasticity to price is found to be around -0.8, which is close to airline demand's price elasticity estimated by Wang et al. (2018).

Table B4 GMM estimation results for airline demand equation with assumed functional forms of $f(s_{it}) = s_{it}, {s_{it}}^2$, or $\sqrt{s_{it}}$

Airline Traffic	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**
$f(s_{it})$		s_{it}			${s_{it}}^2$			$\sqrt{s_{it}}$	
ρ_1	-0.0041***	-0.0055***	-0.00778	-6.56× 10^{-6}***	-8.69× 10^{-6}***	-1.22× 10^{-5}	-1.131***	-1.431***	-1.929
	(0.0013)	(0.442)	(0.048)	(2.46× 10^{-6})	(2.22× 10^{-6})	(-8.32× 10^{-6})	(0.341)	(0.279)	(1.241)
ρ_2	1.986	2.135	2.103	1.882	2.123	2.083	2.043	2.137	2.087
	(9.865)	(5.896)	(6.944)	(9.850)	(5.917)	(6.957)	(9.871)	(5.892)	(6.962)
Yield	-0.733*	-0.784*	-0.820**	-0.711*	-0.772*	-0.840**	-0.744*	-0.797*	-0.846***
	(0.410)	(0.442)	(0.061)	（0.408）	(0.441)	(0.432)	(0.411)	(0.443)	(0.432)
Population	-0.287	-0.285	0.499	-0.377	-0.442	0.502	-0.159	-0.101	0.494
	(0.817)	(0.747)	(0.834)	(0.814)	(0.741)	(0.839)	(0.822)	(0.756)	(0.841)
Income	-0.228*	-0.288**	-0.283**	-0.227	-0.298**	-0.262*	-0.229	-0.273*	-0.258*
	(0.146)	(0.141)	(0.142)	(0.146)	(0.141)	(0.141)	(0.146)	(0.141)	(0.142)
LCC	-0.017	-0.018	-0.0179	-0.017	-0.018	-0.017	-0.017	-0.017	-0.017
	(0.066)	(0.065)	(0.065)	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)	(0.065)
Tourism	0.0105	0.033	0.0602	0.008	0.019	0.077	0.007	0.039	0.079*
	(0.0519)	(0.044)	(0.048)	(0.052)	(0.044)	(0.049)	(0.051)	(0.044)	(0.049)
Spring	0.384**	0.375**	0.382**	0.381**	0.371**	0.391**	0.385**	0.381**	0.392**
	(0.188)	(0.188)	(0.188)	(0.188)	(0.189)	(0.187)	(0.188)	(0.188)	(0.188)
Summer	0.375**	0.374***	0.377**	0.372**	0.372**	0.382**	0.375**	0.376**	0.383**
	(0.177)	(0.188)	(0.176)	(0.177)	(0.177)	(0.187)	(0.177)	(0.176)	(0.175)
Autumn	-0.146	-0.153	-0.150	-0.145	-0.154	-0.148	-0.145	-0.151	-0.148
	(0.231)	(0.229)	(0.228)	(0.231)	(0.230)	(0.229)	(0.231)	(0.229)	(0.228)
Year2011	0.691***	0.706***	0.696***	0.689***	0.709	0.697***	0.691***	0.703***	0.697***
	(0.184)	(0.184)	(0.182)	(0.183)	(0.184)	(0.183)	(0.184)	(0.183)	(0.182)
Year2012	0.729***	0.746***	0.724***	0.729***	0.752***	0.722***	0.726***	0.739	0.723***
	(0.180)	(0.179)	(0.177)	(0.180)	（0.180）	(0.178)	(0.179)	(0.178)	(0.178)
Year2013	0.306***	0.317***	0.287***	0.310***	0.325***	0.281***	0.302***	0.306***	0.280***
	(0.053)	(0.051)	(0.054)	(0.053)	（0.051）	(0.054)	(0.053)	(0.052)	(0.054)
Constant	14.564***	15.109***	9.957*	15.135***	16.116***	9.551	13.969***	14.580***	10.510***

Airline Traffic	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**	**All**	**<850km**	**>850km**
$f(s_{it})$		s_{it}			$s_{it}{}^2$			$\sqrt{s_{it}}$	
	(5.501)	(5.062)	(5.697)	(5.474)	（5.001）	(5.682)	(5.529)	(5.092)	(5.803)
Time trend fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
HSR route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual route fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Observations	1,036	980	966	1,036	980	966	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_{\mathrm{i}}$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.

2. ***<0.01, **<0.05, *<0.10.

3. Standard errors are in parentheses.

Table B5 GMM estimation results for airline price equation

Airline Price	All	<850km	>850km
Passenger	-0.536***	-0.402***	-0.395***
	(0.253)	(0.176)	(0.189)
HHI	0.080***	0.072**	0.074**
	(0.038)	(0.031)	(0.031)
LCC	-0.051**	-0.050*	-0.03
	(0.032)	(0.037)	(0.036)
Tourism	-0.025	-0.018	0.026
	(0.033)	(0.024)	(0.028)
Spring	0.365***	0.315***	0.315***
	(0.136)	(0.110)	(0.109)
Summer	0.329***	0.282***	0.282***
	(0.132)	(0.106)	(0.105)
Autumn	-0.031	-0.022	-0.020
	(0.159)	(0.134)	(0.130)
Year2011	0.510***	0.433***	0.431***
	(0.168)	(0.129)	(0.130)
Year2012	0.502***	0.420***	0.416***
	(0.176)	(0.134)	(0.136)
Year2013	0.132**	0.096***	0.092*
	(0.067)	(0.048)	(0.050)
Constant	4.823	3.405	3.287
	(3.065)	(2.157)	(2.315)
Time trend fixed effect	✓	✓	✓
HSR route fixed effect	✓	✓	✓
Individual route fixed effect	✓	✓	✓
No. of Observations	1,036	980	966

Note:

1. The coefficient of the time-invariant variable, i.e., the airline route distance variable, $\ln Dist\_Air_i$ cannot be identified because the route fixed effect has been controlled. Therefore, we do not report the coefficient for the airline route distance variable in the table.
2. ***<0.01, **<0.05, *<0.10.
3. Standard errors are in parentheses.

Appendix C: Appendix for Chapter 4

C1. Reduced form demand equation estimation

Given the specific form of error term ε_{ijt}, the market share for each product in the market can be uniquely identified from a simple algebraic calculation. Denote s_0 as the market share of non-air travel, then,

$$s_0 = \frac{1}{1+D_t^{\lambda}} \tag{C.1}$$

Then the log of proportion of product j in market t and no air travel is,

$$\ln\left(\frac{S_{jt}}{S_0}\right) = \frac{\boldsymbol{x_{jt}\beta}-\alpha p_{jt}+\xi_{jt}}{\lambda} + (1-\lambda)\ \ln D_t \tag{C.2}$$

And the log of proportion of air travel and no air travel is,

$$\ln\left(\frac{S_t}{S_0}\right) = \lambda \ln D_t \tag{C.3}$$

Combining the above two expressions, we can get,

$$\ln\left(\frac{S_{jt}}{S_0}\right) = \frac{\boldsymbol{x_{jt}\beta}-\alpha p_{jt}}{\lambda} + \left(\frac{\lambda-1}{\lambda}\right)\ln\left(\frac{S_t}{S_0}\right) + \frac{\xi_{jt}}{\lambda} \tag{C.4}$$

Both the ξ_{jt} and $\ln\left(\frac{S_t}{S_0}\right)$ are endogenous as they are obviously correlated to x_{jt} and p_{jt}. Thus the IV estimation is conducted to estimate β, α and λ. The IVs used here are the same as for the BLP estimation.

C2. Derivative of product share to price (Bertrand)

For the simplification of our derivation, first we denote:

$$A_{jt}=e^{\frac{\boldsymbol{x_{jt}\beta}-\alpha p_{jt}+\xi_{jt}}{\lambda}} \tag{C.5}$$

It is straightforward to get the first derivatives for A_{jt} and D_t as:

$$\frac{\partial A_{jt}}{\partial p_{jt}}=\frac{-\alpha}{\lambda}A_{jt},\quad \frac{\partial D_{rt}}{\partial p_{jt}}=\frac{-\alpha}{\lambda}A_{jt},\quad \frac{\partial A_{jt}}{\partial p_{it}}=0,\quad \frac{\partial D_{rt}}{\partial p_{it}}=\frac{-\alpha}{\lambda}A_{it} \tag{C.6}$$

Then the derivative of s_{jt} in its own price p_{jt} is as follows:

$$\frac{\partial s_{jt}}{\partial p_{jt}}=\frac{\partial\frac{A_{jt}D_t^{\lambda-1}}{1+D_t^{\lambda}}}{\partial p_{jt}}=\frac{\left(\frac{-\alpha}{\lambda}\right)\left[\left(A_{jt}\right)^2(\lambda-1)D_t^{\lambda-2}+A_{jt}D_t^{\lambda-1}\right]\left(1+D_t^{\lambda}\right)+\alpha\left(A_{jt}\right)^2\left(D_t^{\lambda-1}\right)^2}{\left(1+D_t^{\lambda}\right)^2}= \tag{C.7}$$

$$\frac{\left(\frac{-\alpha}{\lambda}\right)A_{jt}D_t^{\lambda-2}\left[\left(D_t-A_{jt}\right)\left(1+D_t^{\lambda}\right)+\lambda A_{jt}\right]}{\left(1+D_t^{\lambda}\right)^2}$$

Then the derivative of s_{jt} of the p_{it} is:

$$\frac{\partial s_{jt}}{\partial p_{it}}=\frac{\partial\frac{A_{jt}D_t^{\lambda-1}}{1+D_t^{\lambda}}}{\partial p_{it}}=\frac{\left(\frac{-\alpha}{\lambda}\right)\left[A_{jt}A_{it}(\lambda-1)D_t^{\lambda-2}\right]\left(1+D_t^{\lambda}\right)+\alpha A_{jt}A_{it}\left(D_t^{\lambda-1}\right)^2}{\left(1+D_t^{\lambda}\right)^2}=\frac{\left(\frac{-\alpha}{\lambda}\right)A_{jt}A_{it}D_t^{\lambda-2}\left[\lambda-1-D_t^{\lambda}\right]}{\left(1+D_t^{\lambda}\right)^2} \tag{C.8}$$

C3. Derivative of price to product share for the Nash-Cournot

From reduced form in Appendix C1, we have:

$$p_{jt} = \frac{1}{\alpha}[\boldsymbol{x_{jt}\beta} + (\lambda\text{-}1)\ln\left(\frac{S_t}{S_0}\right) - \lambda\ln\left(\frac{S_{jt}}{S_0}\right) + \xi_{jt}] \tag{C.9}$$

Then it is easy to get the derivative of p_{jt} in its own share s_{jt}:

$$\frac{\partial p_{jt}}{\partial s_{jt}} = \frac{1}{\alpha}\left[(\lambda\text{-}1)\frac{1}{s_t} - \frac{1}{s_0} - \frac{\lambda}{s_{jt}}\right] \tag{C.10}$$

and the derivative of p_{jt} in the share s_{jt}:

$$\frac{\partial p_{jt}}{\partial s_{it}} = \frac{1}{\alpha}\left[(\lambda\text{-}1)\frac{1}{s_t} - \frac{1}{s_0}\right] \tag{C.11}$$

C4. Proof of existence and uniqueness of Fixed Point problem

Denote function $G: D \to D$, where $p_t \in D$. If there exist a constant $\rho < 1$, such that, in some natural matrix norm:

$$\|J_G(p_t)\| \leq \rho, \quad p_t \in D \tag{C.12}$$

where $J_G(p_t)$ is the Jacobian matrix of function G evaluated at p_t, then function G has a unique fixed point p_t^* and fixed-point iteration is guaranteed to converge to p_t^* for any initial guess $p_t^0 \in D$.

$$\|J_G(p_t)\| = \left\|\left(\Omega_t^{-1}(p_t)\right)' s_t(p_t;x_t,\xi_t,\theta_d) + \Omega_t^{-1}(p_t)s_t'(p_t;x_t,\xi_t,\theta_d)\right\| = \left\|1 - \left(\Omega_t^{-1}(p_t)\right)' s_t(p_t;x_t,\xi_t,\theta_d)\right\| = \tag{C.13}$$

$$\left\|1 + \Omega_t^{-1}(p_t)\frac{\partial \Omega_t(p_t)}{\partial p_t}\Omega_t^{-1}(p_t)s_t(p_t;x_t,\xi_t,\theta_d)\right\| < 1$$

The last inequality holds because $\Omega_t^{-1}(p_t)$ is non-negative matrix because $\Omega_t(p_t)$ is non-negative, and $\frac{\partial \Omega_t(p_t)}{\partial p_t}$ is non-positive matrix.

Appendix D: Appendix for Chapter 5

D1. Different effects of runway and terminal congestion

In this Appendix D1, we disentangle the impact of runway congestion on concession demand from that of terminal congestion. Let D_r denote airport runway congestion, and D_t denote terminal congestion. $D_r(Q,K_r)$ is a function of airport passenger volume and the runway capacity K_r, and $D_t(Q, K_t)$ is a function of airport passenger volume and terminal size K_t.

D1.1 Runway congestion

Runway congestion results in flight delay and thus contributes more to a passenger's longer dwell time at the airport after the security check. It is thus more associated with dwell time effect, compared to terminal congestion. Accordingly, the more significant positive dwell time effect of runway congestion helps the term $\frac{\partial T}{\underbrace{\partial D_r}_{>0}}$ to be larger than $\frac{\partial S}{\underbrace{\partial D_r}_{>0}}$, making the positive dwell time effect to dominate the negative stress effect. When we only consider the runway congestion, ceteris paribus, one should be more likely to observe an increase in concession demand with the runway congestion. Therefore, we are more likely to observe $\frac{d(1\text{-}G)}{dD_r}>0$:

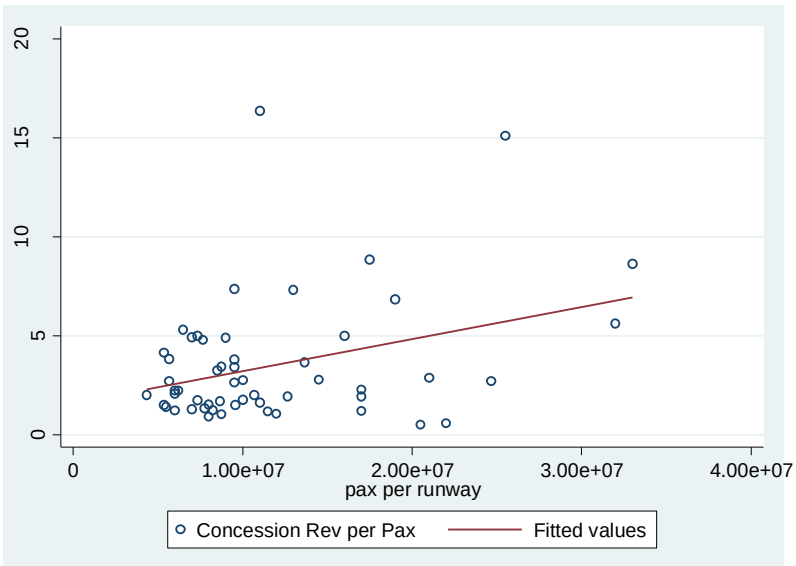
$$\frac{d(1\text{-}G)}{dD_r}=\underbrace{\frac{\partial(1\text{-}G)}{\partial T}}_{>0}\underbrace{\frac{\partial T}{\partial D_r}}_{>0}+\underbrace{\frac{\partial(1\text{-}G)}{\partial S}}_{<0}\underbrace{\frac{\partial S}{\partial D_r}}_{>0}>0 \tag{D.1}$$

According to Eq. (D.2), we are more likely to observe that concession demand to decrease with the more runway capacity:

$$\frac{d(1\text{-}G)}{dK_r}=\underbrace{\frac{d(1\text{-}G)}{dD_r}}_{>0}\underbrace{\frac{dD_r}{dK_r}}_{<0}<0 \tag{D.2}$$

Such conjecture might be supported by the plot of the concession revenue per passenger and the number of passengers per runway as Figure D1, that runway congestion is negatively correlated to concession revenue per passenger.

Figure D1 The relation between number of passenger per runway and per passenger concession revenue



D1.2 Terminal Congestion

Terminal congestion contributes more to stress effect when passengers consume concession services in the terminal. Terminal congestion thus contributes more to stress effect, making $\underbrace{\frac{\partial S}{\partial D_t}}_{>0}$ more likely to be larger than $\underbrace{\frac{\partial T}{\partial D_t}}_{>0}$. Therefore, we are more likely to observe the $\frac{d(1\text{-}G)}{dD_t}<0$,

$$\frac{d(1\text{-}G)}{dD_t}=\underbrace{\frac{\partial(1\text{-}G)}{\partial T}}_{>0}\underbrace{\frac{\partial T}{\partial D_t}}_{>0}+\underbrace{\frac{\partial(1\text{-}G)}{\partial S}}_{<0}\underbrace{\frac{\partial S}{\partial D_t}}_{>0}<0 \tag{D.3}$$

According to Eq. (D.4), we are more likely to observe that concession demand to increase with the increased terminal capacity.

$$\frac{d(1\text{-}G)}{\mathrm{d}K_t} = \underbrace{\frac{\mathrm{d}(1\text{-}G)}{\mathrm{d}D_t}}_{<0} \underbrace{\frac{\mathrm{d}D_t}{\mathrm{d}K_t}}_{<0} > 0 \tag{D.4}$$

This relationship might be supported by the following plot in Figure D2, where the concession revenue per passenger is negatively correlated with the number of passengers per terminal square meter.

Figure D2 The relation between number of passenger per terminal square meter concession revenue per passenger

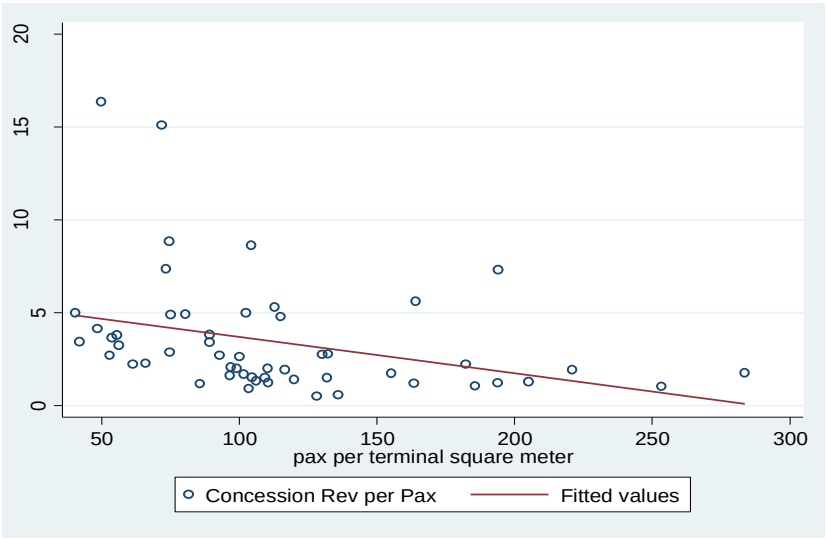
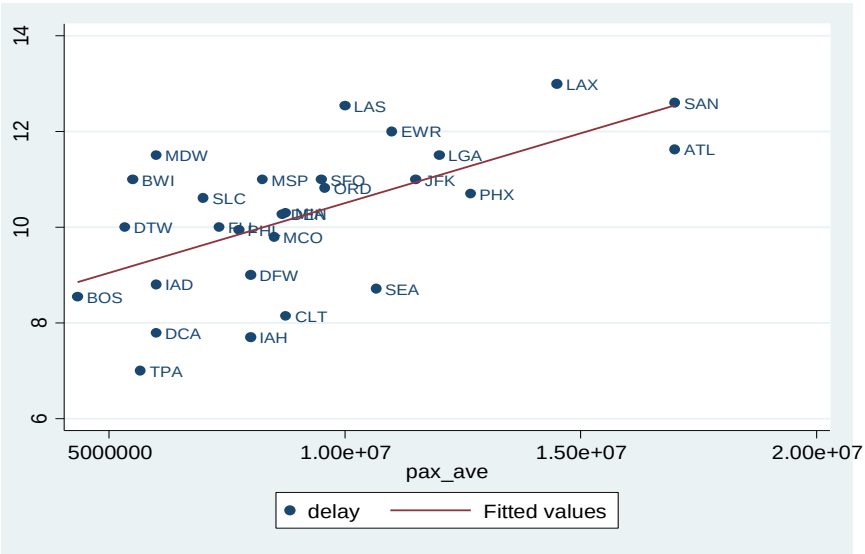


Figure D3 Average flight delay and the average passenger per runway for the US sample airports

(as of the 4th quarter of year 2010)



Note: The flight delay is the average minutes of delay per flight for the US airports, collected from Bureau of Transportation Statistics (BTS) US, for the 4th quarter of year 2010; the "Pax_ave" in the figure is the passenger number per runway.

D2. The effect of concession price on aeronautical charge for private and public airports

For a private airport, we have,

$$\frac{\partial \tau}{\partial r} = -\ [(1 - G(r,D)) - Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}] \tag{D.5}$$

$\frac{\partial\tau}{\partial r}$<0 when congestion is moderate with $\frac{\partial G}{\partial D}$<0; it is possible that $\frac{\partial\tau}{\partial r}$>0 when congestion is severe with $\frac{\partial G}{\partial D}$>0.

For a public airport, we have:

$$\frac{\partial\tau}{\partial r} = -\frac{\partial \mathrm{E}(x|x>r,D)}{\partial r}\left(1 - G(r,D)\text{-}Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}\right) + [\mathrm{E}(x|x>r,D) - c_2]\left[\frac{\partial G}{\partial r} + Q\frac{\partial D}{\partial Q}\frac{\partial^2 G}{\partial D\partial r}\right] - \left[\frac{\partial D}{\partial Q}\frac{\partial}{\partial r}[\frac{\partial}{\partial D}\mathrm{E}(x\ |x>r,\ D)]\right][1\text{-}G(r,D)]Q + \left[\frac{\partial D}{\partial Q}\ \frac{\partial}{\partial D}\mathrm{E}(x\ |x>r,\ D)\right]\ \frac{\partial G}{\partial r}\ Q \tag{D.6}$$

The sign of $\frac{\partial\tau}{\partial r}$ is difficult to predict, no matter $\frac{\partial G}{\partial D}$<0 or $\frac{\partial G}{\partial D}$>0.

D3. Proof of Propositions 5.2 a and 5.2 b

It is assumed that the higher order $D''(Q,K)$ and $B'''(Q)$ are zero and,

$$(\tau_{\text{private}} - \tau_{\text{public}})\ |\ Q,r = \underbrace{\frac{2}{N}vQD'(Q) - \left(1+\frac{2}{N}\right)B''(Q)Q}_{>0} + [\mathrm{E}(x\ |x>r,\ D) - r][1\text{-}G(r,D)\text{-}\mathrm{Q}\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}] + \left(\left[\frac{\partial D}{\partial Q}\frac{\partial}{\partial D}\mathrm{E}(x\ |x>r,\ D)\right]\left(1\text{-}G(r,D)\right)Q \tag{D.7}$$

The term $\frac{2}{N}vQD'(Q)$- $\left(1+\frac{2}{N}\right)B''(Q)Q>0$, and the term

$[\mathrm{E}(x\ |x>r,\ D)\text{-}r][1\text{-}G(r,D)\text{-}Q\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}]+(\left[\frac{\partial D}{\partial Q}\frac{\partial}{\partial D}\mathrm{E}(x\ |x>r,\ D)\right]\left(1\text{-}G(r,D)\right)Q>0$, when congestion is moderate with $\frac{\partial G}{\partial D}$<0, while $(\tau_{\text{private}}\text{-}\tau_{\text{public}})\ |\ Q,r < 0$ when congestion is severe with $\frac{\partial G}{\partial D}$>0. In sum,

when congestion is moderate with $\frac{\partial G}{\partial D}<0$, a private airport should charge a higher aeronautical price than a public airport, but the opposite happens when congestion is severe with $\frac{\partial G}{\partial D}>0$.

Table D1 Sample airports

Asia-Pacific			
Airport code	**Airport name**	**City country**	**Slot control**
AKL	Auckland International Airport	Auckland, New Zealand	Level 3
BKK	Suvarnabhumi Airport	Bangkok, Thailand	Level 3
BNE	Brisbane Airport	Brisbane, Australia	Level 3
CAN	Bai Yun Airport	Guangzhou, China	Level 3
CGK	Jakarta Soekarno-Hatta International Airport	Jakarta, Indonesia	Level 3
DEL	Indira Gandhi International Airport	New Delhi, India	Level 3
HKG	Hong Kong International Airport	Hong Kong, China	Level 3
HND	Haneda Airport	Tokyo, Japan	Level 3
ICN	Incheon International Airport	Incheon, Korea	Level 3
KUL	Kuala Lumpur International Airport	Kuala Lumpur, Malaysia	Level 3
MEL	Melbourne Airport	Melbourne, Australia	Level 3
NRT	Tokyo Narita International Airport	Tokyo, Japan	Level 3
PEK	Beijing Capital International Airport	Beijing, China	Level 3
PVG	Shanghai Pudong International Airport	Shanghai, China	Level 3
SIN	Singapore Changi International Airport	Singapore, Singapore	Level 3
SYD	Sydney Airport	Sydney, Australia	Level 3
Europe			
Airport code	**Airport name**	**City country**	**Slot control**
AMS	Amsterdam Airport Schiphol	Amsterdam, The Netherlands	Level 3
ATH	Athens International Airport	Athens, Greece	Level 3
BRU	Brussels Airport	Brussels, Belgium	Level 3
CPH	Copenhagen Airport Kastrup	Copenhagen, Denmark	Level 3
DUS	Düsseldorf International Airport	Düsseldorf, Germany	Level 3
LGW	London Gatwick International Airport	London, England	Level 3
LHR	London Heathrow Airport	London, England	Level 3
LIS	Lisbon Portela Airport	Lisbon, Portugal	Level 3
MUC	Munich Airport	Munich, Germany	Level 3
MXP	Milan Malpensa Airport	Milan, Italy	Level 3
STN	London Stansted Airport	London, England	Level 3
VIE	Vienna International Airport	Vienna, Austria	Level 3
ZRH	Zurich Airport	Zurich, Switzerland	Level 3

North America Airport code	Airport name	City country	Slot control
ATL	Hartsfield-Jackson Atlanta International Airport	Atlanta, Georgia	
BOS	Boston Logan International Airport	Boston, Massachusetts	
BWI	Baltimore Washington International Airport	Baltimore, Maryland	
CLT	Charlotte Douglas International Airport	Charlotte, North Carolina	
DCA	Ronald Reagan Washington National Airport	Washington, DC	
DEN	Denver International Airport	Denver, Colorado	
DFW	Dallas Forth Worth International Airport	Dallas, Texas	
DTW	Detroit Metropolitan Wayne County Airport	Detroit, Michigan	
EWR	Newark Liberty International Airport	Newark, New Jersey	Level 2
FLL	Fort Lauderdale Hollywood International Airport	Ft. Lauderdale, Florida	
IAD	Washington Dulles International Airport	Washington, DC	
IAH	George Bush Intercontinental Airport	Houston, Texas	
JFK	New York-John F. Kennedy International Airport	New York, New York	Level 3
LAS	Las Vegas McCarran International Airport	Las Vegas, Nevada	
LAX	Los Angeles International Airport	Los Angeles, California	Level 2
LGA	LaGuardia International Airport	New York, New York	
MCO	Orlando International Airport	Orlando, Florida	Level 2
MDW	Chicago Midway Airport	Chicago, Illinois	
MIA	Miami International Airport	Miami, Florida	
MSP	Minneapolis/St. Paul International Airport	Minneapolis, Minnesota	
ORD	Chicago O'Hare International Airport	Chicago, Illinois	Level 2
PDX	Portland International Airport	Portland, Oregon	
PHL	Philadelphia International Airport	Philadelphia, Pennsylvania	
PHX	Phoenix Sky Harbor International Airport	Phoenix, Arizona	
SAN	San Diego International Airport	San Diego, California	
SEA	Seattle-Tacoma International Airport	Seattle, Washington	
SFO	San Francisco International Airport	San Francisco, California	Level 2
SLC	Salt Lake City International Airport	Salt Lake City, Utah	
STL	St. Louis-Lambert International Airport	St. Louis, Missouri	
TPA	Tampa International Airport	Tampa, Florida	
YVR	Vancouver International Airport	Vancouver, British Columbia	Level 3

D4. Proof of Proposition 5.3

In this Appendix D4, we prove that Proposition 5.3 also holds for concession revenue per passenger, $r(1\text{-}G)$.

For a private airport,

$$\frac{\partial r(1\text{-}G(D(K,Q),r)}{\partial Q}=\left(1\text{-}G(D,r)\right)\frac{\partial r}{\partial Q}\text{-}r\frac{\partial G}{\partial Q}=\left(1\text{-}G(D,r)\right)\frac{\partial r}{\partial Q}\text{-}r\left[\frac{\partial G}{\partial D}\ \frac{\partial D}{\partial Q}+\frac{\partial G}{\partial r}\ \frac{\partial r}{\partial Q}\right] \tag{D.8}$$

$$=\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)\frac{\partial r}{\partial Q}\text{-}r\frac{\partial G}{\partial D}\ \frac{\partial D}{\partial Q}=\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)\frac{\frac{\partial G}{\partial D}\frac{\partial D}{\partial Q}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r\partial D}\frac{\partial D}{\partial Q}}{\text{-}\left[2\frac{\partial G}{\partial r}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r^2}\right]}$$

$$\text{-}\,r\frac{\partial G}{\partial D}\ \frac{\partial D}{\partial Q}=\left[\frac{\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)}{\text{-}\left[2\frac{\partial G}{\partial r}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r^2}\right]}\text{-}r\right]\frac{\partial D}{\partial Q}\frac{\partial G}{\partial D}+\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)\frac{(r\text{-}c_2)\frac{\partial^2 G}{\partial r\partial D}\frac{\partial D}{\partial Q}}{\text{-}\left[2\frac{\partial G}{\partial r}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r^2}\right]}$$

As long as $1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}>0$, we have the term $\frac{\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)}{\text{-}\left[2\frac{\partial G}{\partial r}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r^2}\right]}\text{-}r<0$ and

$\left(1\text{-}G(D,r)\text{-}r\frac{\partial G}{\partial r}\right)\frac{(r\text{-}c_2)\frac{\partial^2 G}{\partial r\partial D}\frac{\partial D}{\partial Q}}{\text{-}\left[2\frac{\partial G}{\partial r}+(r\text{-}c_2)\frac{\partial^2 G}{\partial r^2}\right]}>0$, thus making the $\frac{\partial r(1\text{-}G(D(K,Q),r)}{\partial Q}>0$ when $\frac{\partial G}{\partial D}<0$, and making it is possible for $\frac{\partial r(1\text{-}G(D(K,Q),r)}{\partial Q}<0$ when $\frac{\partial G}{\partial D}>0$.

For a public airport,

$$\frac{\partial r(1\text{-}G(D(K,Q),r)}{\partial Q} = \left(1\text{-}G(D,r)\right)\frac{\partial r}{\partial Q}\text{-}r\frac{\partial G}{\partial Q} = \left(1\text{-}G(D,r)\right)\frac{\partial r}{\partial Q}\text{-}r\left[\frac{\partial G}{\partial D}\ \frac{\partial D}{\partial Q} + \frac{\partial G}{\partial r}\ \frac{\partial r}{\partial Q}\right] \quad \text{(D.9)}$$

Because $\frac{\partial r}{\partial Q}$ =0 referring to Eq. (6.15), $\frac{\partial \mathrm{r(1\text{-}G(D(K,Q),r)}}{\partial \mathrm{Q}} = -r\frac{\partial \mathrm{G}}{\partial \mathrm{D}}\ \frac{\partial \mathrm{D}}{\partial \mathrm{Q}}$. Thus $\frac{\partial r(1-G(D(K,Q),r)}{\partial Q} > 0$ when $\frac{\partial G}{\partial D} < 0$, and $\frac{\partial r(1-G(D(K,Q),r)}{\partial Q} < 0$ when $\frac{\partial G}{\partial D} > 0$.