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Modelling Emissions Reduction Strategies for Passenger Air Transport

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Thesis submitted to
The Faculty of Built Environment, The Bartlett,
University College London
for the degree of Doctor of Philosophy

APR 2020

Declaration

I, Bojun Wang, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis. This dissertation contains around 55,000 words with 30 figures and 16 tables.

Singed: Bojun Wang

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Abstract

This dissertation aims to evaluate the potential for and the effectiveness of two strategies that could reduce carbon dioxide (CO₂) emissions from passenger aviation. The two strategies consist of market-based measures (MBMs) and the substitution of high-speed rail (HSR) for air transport. To assess the first mitigation strategy an econometric, itinerary-based airfare model, which explicitly captures airline operating costs, is developed and estimated for different world regions. Based on the estimated cost pass-through elasticities, the impact of a carbon tax is tested for the European and Asia-Pacific markets. Because of the higher cost pass-through elasticity in the Asia-Pacific market, a carbon tax would lead to higher airfares, lower demand, and thus greater emissions reductions in the Asia-Pacific compared to the European market. For the second mitigation strategy, i.e. the HSR substitution for air transport, this dissertation takes China's transportation network as a case study. In a first step, an empirical study explores how airline supply has already been affected by the introduction of HSR since 2008. The results show that the HSR substitution has led to operational CO₂ emissions savings from aviation in the order of 6.52-7.44 million tonnes over the period 2009-2015, depending on assumptions on the electricity intensity of Chinese HSR trains. In a second step, the dissertation explores how the enhanced introduction of HSR may affect future aviation CO₂ emissions. To accomplish this objective, the future demand for inter-city high-speed transportation between 2016 and 2050 and the mode shares of HSR and air travel are estimated with an econometric model. The projected aviation demand under the planned 2025 HSR network is then compared against the demand under the 2015 HSR network. The marginal net savings of lifecycle CO₂ emissions resulting from the HSR substitution

are calculated from the “avoided” emissions in aviation and the additional emissions generated from transporting the diverted demand by HSR. The results show that, if China continues decarbonizing its power generation sector and achieves zero-carbon power generation in 2050, the cumulative marginal net savings of CO₂ emissions could be at 736-960 million tonnes, depending on assumptions on China’s future population, GDP per capita, and jet fuel prices. The annual average of this amount between 2016 and 2050 are equivalent to 39-50% of the 53.8 million tonnes CO₂ emissions from domestic aviation in 2015.

Impact Statement

The research presented in this dissertation contributes important knowledge to both inside and outside academia. The key benefits that this work delivers inside academia are fourfold. Firstly, it is one of the first studies that provide empirical evidence of airlines' cost pass-through behaviour, which can be used in future research that otherwise would have to rely on presumed cost pass-through rates when evaluating the system-wide impacts of market-based environmental policies on aviation. Secondly, it empirically demonstrates positive net operational emissions savings through the HSR substitution for air transport in China since it introduced its HSR system, using an innovative method to simulate the emissions savings simply based on airline supply data. Thirdly, it presents the most comprehensive CO₂ emissions lifecycle inventories for the Chinese air transport and HSR systems published to date, taking into account the competition effects between HSR and aviation. Fourthly, the airfare model developed in this work is a key component of an open-source large-scale aviation systems model AIM2015 that can be used freely by hundreds of researchers.

The potential impacts of this work to the outside of academia are also significant. First of all, as mentioned above, the open-source AIM2015 which contains the airfare model developed in this research can be also used by industry practitioners. Further, findings from this work provides important insights for policy makers to evaluate aviation mitigation options discussed in this dissertation. Lastly, the comprehensive assessments of this research on the lifecycle emissions inventories of air transport and HSR, as well as the resulting net emissions savings inventory from

modal substitution provide valuable evidence to support proposals or government plans that are in favour of future infrastructure investments on the HSR network.

The impact of this dissertation has been brought through disseminating outputs through presentations in high-level international academic conferences and publications with leading peer-reviewed journals. This work has been presented in the following conferences:

- 97th Transportation Research Board Annual Meeting, “Environmental Issues in Aviation” session, Washington DC, U.S., 13-17 January 2019;
- 96th Transportation Research Board Annual Meeting, “Geopolitics and Commercial Aviation” session, Washington DC, U.S., 7-11 January 2018;
- 21st Air Transportation Research Society (ATRS) World Conference, Antwerp, Belgium, 5-8 July 2017.

In addition, each of the main chapters in this thesis has been published or submitted for review in leading peer-reviewed journals:

- Research findings from Chapter 4 are published as:
Bojun Wang, Aidan O’Sullivan, Lynnette Dray, Andreas Schäfer. “Modelling Airline Cost Pass-through within Regional Aviation Markets”, *Transportation Research Record*, 2018, paper Number 18-04368, pp. 1-12. Peer-reviewed by The Standing Committee on Aviation Economics and Forecasting.
- Research findings from Chapter 5 are published as:
Bojun Wang, Aidan O’Sullivan, Andreas Schäfer. “Assessing the Impact of High-speed Rail on Domestic Aviation CO₂ Emissions in China”, *Transportation Research Record*, 2019, paper Number 19-05366, pp. 1-13. Peer-reviewed by The Standing Committee on Environmental Impacts of Aviation.
- Research findings from Chapter 6 is ready for submission as:
Bojun Wang and Andreas Schäfer. “Modelling Net Savings of China’s Aviation Lifecycle CO₂ Emissions from High-Speed Modal Substitution”.

Acknowledgements

Through the journey of my PhD in the past four years, I have been fortunate enough to have great supports and encouragement from many people. For that I would like to acknowledge each of these individuals who have made this work possible.

First of all, I am forever grateful to my supervisors, Professor Andreas Schäfer and Dr. Aidan O’Sullivan, who have kindly provided tremendous help and guidance throughout the course of my PhD. Their wealth of knowledge and selfless giving of time have been invaluable to me. Indeed, what I have learnt from them goes beyond how to become an outstanding researcher but to become a better individual as well. Reflecting on how far I’ve come from my first year, it is their exceptional insights and constructive challenges that have pushed me to have this determination and strong mental fabric to independently solve those challenges in my research. Last but not least, I thank them for all the beers that they’ve bought me at pubs over the past four years – one of the many good things for being their student.

I also acknowledge my colleagues in the Air Transportation Systems Lab: Dr. Doyme Khan and Dr. Lynnette Dray for the helpful discussions and comments on this work during our weekly meetings.

My PhD was funded through the Chinese Scholarship Council and the ACCLAIM project grant from the UK Engineering and Physical Sciences Research Council (EPSRC). Their support is gratefully acknowledged. Meanwhile, my sincere gratitude also to the China Railway Corporation for kindly providing the high-speed rail data to this work.

My family has given me the most unconditional love and support throughout this journey. Mom and dad, you have always tried everything you can to support us

for pursuing our dreams, without you I would have no way to be where I am standing right now. Bowen, my lifelong buddy, all the ups and downs I have been through during this tough and very special journey, you are always there and always feeling the same way that I feel. For that, I give you 3 percent share of my success in this PhD. Jiale and Yanchen, thanks for becoming my family. It always gives me endless joy and encouragement when watching the little boy doing whatever stupid yet incredibly adorable things during our skypes. I love you all so much.

My heartfelt thanks also to those closest friends whom I shared unique memories with at various stages of the past four years, to name a few, Dai, Lao Bi, Jun Jun, Feiyang, Yue, Haizhou, Yifei, Dr. Li Lv, Zoe, and Sui. Because of you guys I have never felt that this is a journey on my own. Thank you.

Finally, this dissertation is for grandpa. I hope you are proud in the heaven. Always love you.

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Acronyms and Abbreviations

AIM	Aviation Integrated Model
BTS	Bureau of Transportation Statistics, United States
CAHSR	California High-Speed Railways
CHSR	China's High-Speed Railways
CO ₂	Carbon Dioxide
CORSIA	The Carbon Offsetting and Reduction Scheme for International Aviation
DOT	Department of Transport, United States
EEA	European Economic Area
EIA	Energy Information Administration, United States
ETS	Emissions Trading Schemes
EU	European Union
EI	Energy Intensity
EF	Emission Factor
FAA	Federal Aviation Administration, United States
F2SLS	Feasible Generalised Two-stage Least Squares
GDP	Gross Domestic Profit
GHG	Greenhouse Gases
HHI	Herfindahl-Hirschman Index
HSR	High-speed Rail
IATA	International Air Transportation Association
ICAO	International Civil Aviation Organization
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental Variable
kWh	Kilowatt hour
LCC	Low Cost Carrier
LDV	Light-Duty Vehicle
MBMs	Market-based Measures
MJ	Mega-Joules
MNS	Marginal Net Savings
MtCO ₂	Million tonnes of CO ₂ emissions
MTOW	Maximum take-off weight

NO _x	Nitrogen oxides
O ₃	Ozone
OECD	Organisation for Economic Co-operation and Development
O-D	True origin-ultimate destination
OLS	Ordinary Least Squares
pkm	Passenger-Kilometres
PKT	Passenger-Kilometre-Travelled
PM _{2.5}	Fine particular matter
PMT	Passenger-Mile-Travelled
PTE	Pass-through Elasticity
RPK	Revenue Passenger Kilometres
SUR	Seemingly Unrelated Regression
T&D	Transmission and Distribution
TSLS	Two-stage Least Squares
UIC	Union Internationale des Chemins de fer (International Union of Railways)
UN	United Nations
U.S.	United States
VKT	Vehicle-Kilometre-Travelled
VMT	Vehicle-Mile-Travelled
VOT	Value of Time
WTP	Willingness to Pay

Chapter 1 Introduction

1.1 Background

Innovations in commercial aircraft technology since the early 1950s, represented by the development of the jet engine, have revolutionised long-distance intercity transportation. For the first time, people and goods were moved over long distances not over land and sea but by air, with much higher speed. Since then, demand for commercial air travel in the United States has rapidly taken over from rail in the mid-1950s and from automobiles in about 1960 to become the most important mode of intercity passenger travel, thanks to technological development and government investments in aviation infrastructure (Schäfer et al., 2009). Similar growth trends in commercial aviation are found in other industrialised countries and regions. As shown in Figure 1-1, historically, commercial air travel has experienced a 9% per year growth worldwide from almost zero in 1950 to about 4,000 billion passenger kilometres (pkm) in 2005. Driven by an increasing global gross domestic product (GDP) and by people's desire for faster travel, the rapid growth in passenger air transport demand is expected to continue during the next decades. According to forecasts by both Airbus (2017) and Boeing (2017), from 2017 to 2036, global aviation demand will grow by around 4.5% per year.

Indeed, air travel by overcoming national and continental boundaries has become a symbol of globalization. The rapid development of the air transport sector contributes significantly to global economic prosperity. According to the International Air Transport Association (IATA, 2017), in 2014, aviation industry generated a total

of \$2.7 trillion economic impact (direct, indirect, induced and tourism-connected), accounting for around 3.5% of world's GDP. Meanwhile, it also supported a total of 62.7 million jobs globally (comparable to the United Kingdom's population in 2014), including 9.9 million direct jobs and 52.8 million indirect, induced, and tourism-related jobs.

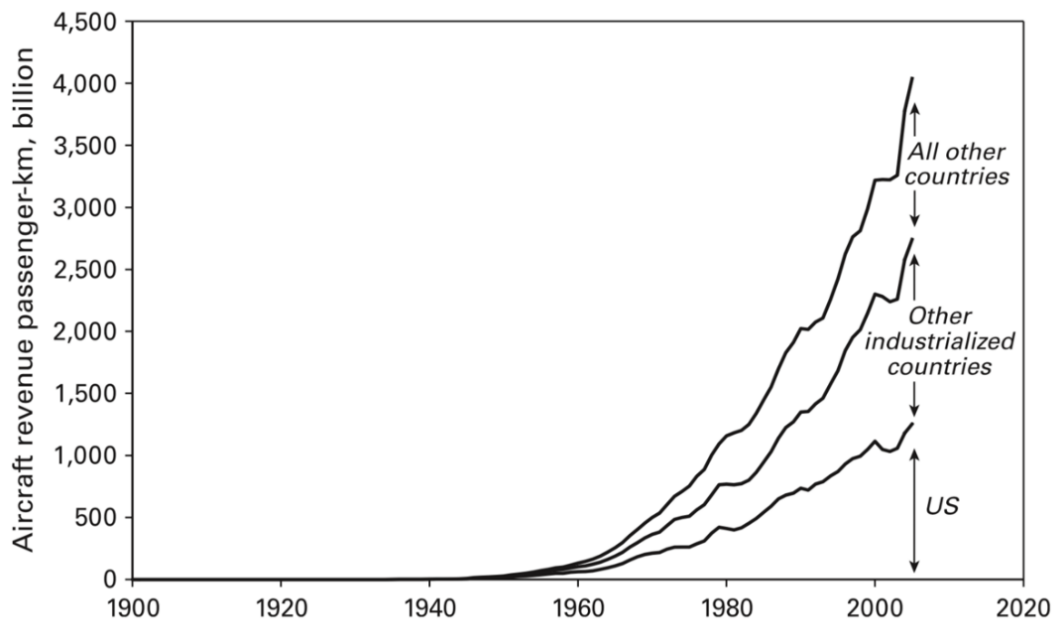


Figure 1-1. Historical growth of world commercial passenger aviation, 1900-2005 (source: Schäfer et al, 2009).

Despite the significant economic benefits that aviation has generated, the rapid growth of the airline industry also comes at an environmental cost. The growing air traffic leads to increasing negative impacts on the environment including air quality, noise, and climate change (IPCC, 1999). This dissertation focuses primarily on the climate change impacts of passenger air transport. Commercial air transportation has been a highly oil-dependent industry, where petroleum-based jet fuels are nearly the exclusive source of transport energy. Owing to combustion of jet fuel, aircraft is a major emitter of carbon dioxide (CO₂). In 2015, the global aircraft fleet consumed 276 million tonnes of jet fuel, which accounted for 7% of global oil products (EIA, 2017a).

Directly proportional to jet fuel combustion, CO₂ emissions from aircraft contributed to 2.7% of the total energy-related emissions in 2015 (Schäfer, et al. 2018). According to the Intergovernmental Panel on Climate Change (IPCC, 1999), CO₂ emissions will increase radiative forcing and cause increases in global average temperature, and such effects will last for hundreds of years. Furthermore, it is found that the non-CO₂-related emissions have warming impacts at about the same magnitude to aircraft CO₂ emissions, thus approximately doubling aviation's contribution to climate change (Lee et al., 2009; Dorbian et al. 2011; Brasseur et al., 2016).

As mentioned earlier, besides its climate change effects, aviation also produces other environmental impacts. For instance, nitrogen oxides (NO_x) and particulate emissions in the vicinity of airports have significant negative effects on local air quality and human health (Graham et al., 2009). As reported by Yim et al. (2015), the aviation-attributable fine particulate matter (PM_{2.5}) and ozone (O₃) will lead to about 16,000 premature mortalities every year globally. Barrett et al. (2010) estimated the concentration of PM_{2.5} due to global aviation emissions and found that global aircraft emissions cause around 10,000 premature deaths per year, with 80% due to cruise emissions. Additionally, previous research have also found that aircraft noise results in adverse health impacts and premature mortality among the affected population, especially near airports (Wolfe et al., 2017).

Due to the large and still growing demand for air transport, aviation emissions could increase significantly over current levels by 2050, in one scenario representing up to 22% of global CO₂ emissions if no mitigation actions are taken (European Parliament, 2015). In order to address this issue, the aviation industry has adopted various measures to reduce emissions. For example, fuel burn per revenue passenger kilometre (RPK) of the U.S. narrow-body aircraft fleet could be reduced by around 2%

per year from 2012 to 2050 at zero marginal costs, with oil prices between \$50 and \$100 per barrel (Schäfer, et al., 2016). However, these improvements will possibly be outpaced by the anticipated growth in global aviation demand at 4.5% per year as described earlier; therefore, extra mitigation options would be required for reducing absolute levels of CO₂ emissions from the air transport sector.

Aircraft emissions could be reduced through technological improvements (Schäfer, et al., 2016, Table 1) that aim to achieve lower engine-specific fuel consumption, lower aircraft structure weight, and greater lift-to-drag ratio. Based on this principle, aviation emissions could be reduced by retrofitting existing aircraft and introducing new designs for next-generation aircraft. In addition, replacing petroleum-based jet fuel by low-carbon fuels such as biomass-based synthetic fuels could partially decouple CO₂ emissions from aviation growth. Furthermore, airlines can reduce emissions through better air traffic management measures that aim to reduce the unnecessary excess distance an aircraft flies (Schäfer, et al., 2016, Table 2). Lastly, improvements in airline operations that increase aircraft load factor or reduce engine-specific fuel consumption along with the fuel weight will also contribute to CO₂ emissions reduction in aviation (Schäfer, et al., 2016, Table 3).

1.2 Market-based Measures for Emissions Mitigation

The mitigation options described above are all technology-related and have been rigorously assessed in previous research (Schäfer, et al., 2016). However, they are still insufficient to achieve a carbon-neutral growth from 2020 onwards for international aviation, which accounts for around 65% of total emissions of the aviation sector (ICAO, 2015). As shown in Figure 1-2, according to the International

Civil Aviation Organization (ICAO, 2013), in order to achieve a carbon neutral growth in international aviation from 2020, other important complementary tools are required, such as the market-based measures (MBMs) for emissions reduction in air transport.

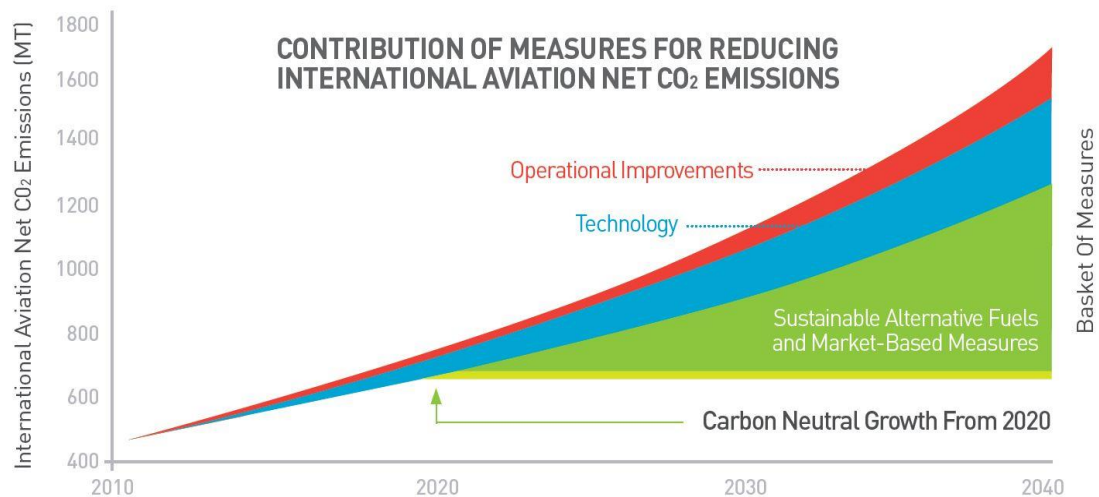


Figure 1-2. Potential mitigation measures required to achieve carbon-neutral growth in international aviation by 2020 (source: ICAO, 2015).

Market-based measures (MBMs), as price-based instruments that complement technological and operational improvements in reducing impact of aviation on climate change, put a price on aircraft emissions. The aim of MBMs is to provide airlines with both flexibility and incentives to limit CO₂ emissions due to the increased cost of emitting. Fuel taxes are the simplest and most common form of MBMs where airlines are obligated to pay a tax based on the total amount of fuel consumed. Another form of MBMs is a “cap-and-trade” mechanism, where airline emissions are “capped” over a certain period. Emissions allowances are created that equal the amount of emittable CO₂. Depending on whether it is an open or closed trading system, airlines are allowed to trade these emission permits within the aviation sector or across different industries with a marketable price (Kolstad, 2009; Hoffmann, 2011) when they manage to emit less than the total allowances obtained. Carbon-offsetting is another form of MBMs that requires airlines to compensate their emissions (instead of directly limiting

emissions under a mandatory cap) by purchasing credits generated from projects that reduce CO₂ emissions in other industries or regions across the world (ICAO, 2016).

One of the most well-known MBMs in the aviation sector is the European Emissions Trading Schemes (EU ETS), which is based on the cap-and-trade mechanism. In 2012, the European Union unilaterally decided to include emissions generated by all flights to, from, and within the European Economic Area (EEA) into the EU ETS (European Commission, 2016). Due to opposition from many non-EU countries, this decision was amended in 2014 to include flights only within the EEA, on the condition that the ICAO could deliver a global market-based mechanism addressing international aviation emissions by 2016 (theguardian, 2013). After assessing a number of MBMs (ICAO, 2013), in 2016, the ICAO reached historic consensus on implementing a global market-based scheme to offset CO₂ emissions from international air transport (ICAO, 2016). The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) will come into force in 2021 to address any increase in total CO₂ emissions from international air transport above the 2020 level, with states participating on voluntary basis until 2027 (ICAO, 2016).

Regardless of the specific MBM, airlines will adjust to the higher fuel cost resulting from the MBMs through changes in technology and operations and through modifying airfares. In order to understand the effectiveness of applying the MBMs in the aviation sector, this adjustment mechanism needs to be fully assessed. In particular, the price penalties caused by the MBMs are expected to affect both the supply and the demand side of the airline industry. If airlines completely absorb such price penalties, their profits might be negatively affected due to increased operating costs. If, instead, airlines fully pass the increased fuel cost onto passengers, air travel may become

economically less attractive because of higher airfares. Thus, passenger demand could decrease, which leads to lower CO₂ emissions.

In order to evaluate the amount of emissions that could be reduced from introducing a market-based policy in the airline industry, the potential impacts of the MBMs on both airline supply and demand must be understood in detail. This requires an empirical assessment of the extent to which airlines would pass the increased costs onto passengers through airfares and how passengers would respond to the increased fares in various regional markets. There does not exist any analysis thus far on the pricing response to increased operating costs in the air transport sector. The key shortcoming of previous research is that operating costs have not been explicitly captured in the existing airline pricing models and thus the effects of costs on airfares are uncertain. By not modelling these effects, the previous research had to assume how airlines would adjust airfares in response to changes in fuel costs, thus resulting in significant uncertainties when assessing the effectiveness of MBM policies. In order to rigorously evaluate the mitigation potential of MBMs in the aviation sector, the cost effects on airline pricing behaviour need to be modelled explicitly, from which the cost pass-through of airlines to passengers could be estimated.

1.3 Emissions Mitigation through Mode Substitution

Emissions reduction in aviation can also be attributed to policies that affect passenger mode choice to travel less by air transport at system level, leading to less significant growth in future aviation demand. As suggested by Greene and Schäfer (2003), encouraging shifting traffic from air transport to modes with low emission rates is one of such system-wide policies. Compared to the mitigation measures that

are directly applied to the aviation sector, policies that aim to improve system-wide energy efficiency could be more challenging as they may require huge infrastructure investments.

Due to the emergence of high-speed rail (HSR), passengers have an alternative high-speed transport mode to aviation. Since 1964, when the world's first HSR, the Tokaido Shinkansen, was launched in Japan between Tokyo and Osaka, the HSR system has expanded considerably, first in Japan, and then in Europe and several Asian countries. Despite a comparatively late start of its first HSR line in 2007, China has rapidly developed the world's largest HSR network in the past decade. By June 2018, HSR in China has accounted for almost 65% of the world's total HSR track length (UIC, 2018). In 2018, China, Japan, France, Spain, Germany, South Korea, Turkey, United States, and Taiwan together account for more than 95% of the world's total HSR track length (UIC, 2018). By 2025, the length of HSR lines worldwide is expected to increase to 54,550 km, more than doubling the 2015 level (UIC, 2018).

As mentioned earlier, air transport heavily depends on petroleum fuels as energy source. In contrast, HSR is powered by electricity. Therefore, depending on the power generation mix, substituting HSR for air transport has a potential to reduce emissions from the aviation sector. Nonetheless, there are two major challenges in this area. Firstly, assessing the traffic shift from one transport mode to the other requires modelling passengers' mode choice for travels at system scale, which is the building block to compare the losses and gains in terms of emissions reduction between the two high-speed transport modes. Given that HSR is a relatively new transport mode, there is limited research focusing on this aspect due to data availability. Secondly, assessing the system-wide savings in CO₂ emissions from modal substitution must compare "avoided" emissions from the low-efficient mode against "additional" emissions from

the high-efficient mode. This requires a rigorous approach that evaluates the lifecycle emissions of both modes and calculates the net climate impacts of the mode substitution based on the lifecycle inventories. Neither of the two challenges described above has been properly addressed in existing literature. In particular, since China has developed very large networks for both HSR and aviation systems, a case study of China's HSR substitution for air transport from a lifecycle perspective would provide valuable insights on the extent to which the high-speed modal substitution as a system-wide mitigation strategy could contribute to emissions reduction in passenger air transport sector.

1.4 Thesis Outline

In order to support informed policy with respect to emissions reduction from passenger air transport sector, this dissertation applies econometric models (i.e. regression models, gravity models, and discrete choice models) and mathematical simulations to evaluate the potential for and the effectiveness of the two strategies described in this chapter. The two strategies consist of market-based measures (MBMs) and the substitution of high-speed rail (HSR) for air transport.

Chapter 2 provides a detailed review of the literature available on existing models for airline pricing, cost pass-through analysis, and the modal substitution between air travel and HSR. The review identifies a gap in the literature in the area of empirically assessing airline cost pass-through behaviour under the market-based emission reduction measures, and in the area of evaluating the mitigation potential for mode substitution of HSR for air transport, with a focus on China's HSR system.

Accordingly, Chapter 3 describes the research questions and corresponding research objectives of the dissertation.

Chapter 4 addresses the research gap identified with respect to airlines' cost pass-through behaviour. This leads to the development of an airline pricing model that explicitly captures the effects of airline operating costs on airfares, model estimation for different regional airline markets, and interpretation with respect to the estimated cost pass-through elasticities for airfares. The chapter concludes by simulating the impacts of introducing a carbon tax on airfares, air travel demand, and CO₂ emissions in two major regional markets with distinct estimated cost pass-through elasticities.

Chapter 5 presents an empirical analysis on the direct impacts of HSR entries on airline supply and associated operational emissions savings, using China's HSR network as a case study. With the data on airline supply in terms of total seats capacity between 2000 and 2015, it reveals Chinese airlines' operational responses to HSR competition by comparing the total seats available on routes with and without HSR on a year-by-year basis. The cumulative historical operational emissions savings from HSR substitution for air transport over the period of 2009 to 2015 is estimated. Finally, a sensitivity analysis is conducted to assess how much additional savings could be achieved compared to the historical savings, if China had lower carbon intensity of power generation over the same period.

Chapter 6 explores this topic further by projecting the lifecycle net CO₂ emissions savings resulting from the planned enhanced HSR network in China, compared to the existing 2015 HSR network. It develops an econometric model that projects future demand for inter-city high-speed transportation between 2016 and 2050 and the mode shares of air travel and HSR, taking into account the competition between the two transport modes. The projected aviation demand under the future

planned 2025 HSR network is then compared against the baseline case with the 2015 HSR network. Finally, this chapter assesses the lifecycle CO₂ emissions (including emissions not only from vehicle operations but also from manufacturing, construction, and fuel production) resulting from the projected demand for both aviation and HSR systems in China. The marginal net savings of lifecycle CO₂ emissions are then calculated from the “avoided” emissions in aviation and the additional emissions generated from transporting the passengers shifted from air transport by HSR.

The conclusions of the research are presented in Chapter 7. They suggest that both strategies assessed in this dissertation could be important complementary tools in reducing emissions from the aviation sector. Despite some inevitable limitations due to data availability, findings from this research could help policy makers to evaluate the potential contributions of adopting these strategies with more certainty. The chapter concludes with the contributions to the existing literature and some recommendations for future research.

Chapter 2 Literature Review

This chapter reviews the existing literature on four individual topics that drive the research questions this dissertation aims to address. In Section 2.1 a literature review is presented of previous airline pricing models, with key determinants of airline airfares summarized from a literature survey. It shows that airline operating costs are not explicitly captured by any of these pricing models. Section 2.2 then reviews existing literature on cost pass-through, with a focus on the economic theory behind this behaviour and previous approach to reflect airlines' pricing responses to market-based environmental policies for aviation. It reveals that the effectiveness of market-based measures in the airline sector is highly uncertain due to a lack of empirical evidence on airlines' cost pass-through in existing literature. Section 2.3 surveys the literature on high-speed rail (HSR) substitution for air transport. It starts with a comparative study on energy intensities across different transport modes particularly for HSR and air transport, and then reviews previous literature on the competition between HSR and aviation. This is followed, in Section 2.4, by a summary of existing studies on lifecycle assessment of CO₂ emissions from both transportation modes, with an emphasis on the importance of accounting for both operational and non-operational emissions in comprehensively understanding the environmental impacts of the HSR substitution for air transport. Finally, conclusions and identified gaps are presented in Section 2.5.

2.1 Existing Models for Airline Pricing Behaviour

In this section, the complexities of airline pricing behaviour are firstly discussed, followed by a review of existing airfare models and the most commonly used influential factors that determine airline airfares.

2.1.1 The complexities of airline pricing behaviour

Airline pricing behaviour is highly complex. The market-equilibrium airfare price for an individual Origin-and-Destination (O-D) market cannot be determined by directly comparing supply and demand, due to the “dichotomy of demand and supply” (Belobaba, 2009). Specifically, from the supply side, one flight segment often provides a joint supply of seats to many O-D markets simultaneously. Thus, the total number of seats on a flight segment cannot represent the “supply” of a single O-D market, nor is it practical to determine accurately the actual number of seats supplied to each O-D market (Simpson & Belobaba, 1992). From the demand side, given that passengers originating at *A* and destined for *B* can choose many itinerary options (non-stop, one-stop, or more stops), the “demand” of a single O-D market is not simply the total number of passengers on non-stop flights between *A* and *B*, but all passengers in this O-D market, regardless of the specific itinerary type they chose to fly (Belobaba, 2009). As a result, this dichotomy of demand and supply makes it inherently impossible for airlines to determine if the market is in equilibrium, and whether the price of airfare is too high or too low in a given O-D market.

Furthermore, airlines apply a combination of cost-, demand-, and service-based pricing principles, which involves both price discrimination (same product, same cost of production, but different willingness to pay) and product differentiation

(different products/qualities, different costs of production, i.e. first class vs. economy class) (Belobaba, 2009). Different levels of fares are then distributed to distinct number of seats on a flight in order to maximize airline revenue, a strategy known as “Revenue Management”, which is out of the scope of this thesis. In addition, the extremely competitive nature of the airline market, especially since the deregulation of the airline industry (in 1978 in the U.S. and by 1997 in Europe) and the emergence of Low-Cost Carriers (LCCs) on short-haul routes in the 2000s, makes airlines set airfares not just based on their own characteristics, but also in consideration of the characteristics of other competitors. All of the above factors make it very challenging to fully understand airline’s pricing behaviour.

2.1.2 Previous airline pricing models

Regression models have been most widely adopted in the previous airline pricing literature. Various researchers focused on different sets of factors in previous regression models to understand their effects on airfares. With the exception of a few studies on the European airline market (Malighetti, et al., 2010; Alderighi, et al., 2011), previous airfare models have almost exclusively focused on the U.S. domestic airline market, for which the most complete airline-specific airfare data is publicly available from the U.S. Department of Transportation’s Origin and Destination Survey Databank 1A/1B (BTS, 2016) on a route-level (a 10% sample of fares over an entire quarter). As a result, airline pricing behaviour in other airline markets is relatively poorly understood. Previous literature has assessed various factors that have an impact on airline pricing, and based upon a literature survey, Table 2-1 summarizes the most commonly used explanatory variables regressed over airfares and their estimated signs from the existing airfare models.

Table 2-1. Literature survey on key factors included in previous airfare models.

Study	Dependent variable	O-D distance	Market concentration	Passenger demand	Flight frequency	Market Share	Load factor	LCCs (dummy)	Tourism (dummy)	Slot control (dummy)	Hub airport (dummy)
Borenstein (1989)	$\ln(Fare)_{ij}$	+	+		+	+	-		-		
Morrison & Clifford (1989)	$Fare_{ij}$	+	+							+	+
Brueckner et al. (1992)	$\ln(Fare)_{ij}$	+	+	-		-			-		
Drenser et al. (1996)	$Yield_{ij}^*$	-	+	+				-	-	+	
Morrison et al. (2001)	$\ln(Fare)_{ij}$	+						-			+
Bitzan & Chi (2006)	$\ln(Fare)_{ij}$	+	+			+	-	-	-	+	
Vowles (2006)	$Fare_{ij}$	+		-				-			
Hofer et al. (2007)	$\ln(Fare)_{ij}$	+	+	-		+	-	-	-	+	
Chi & Koo (2009)	$Yield_{ij}$	-	+		+	+	-	-	-		+
Cho et al. (2002)	$Yield_{ij}$	-		+				-	-	-	
Zhang et al. (2013)	$\ln(Fare)_{ij}$	+		-				-	-	-	
Brueckner et al. (2013)	$\ln(Fare)_{ij}$	+							-		
Zou & Hansen (2014)	$\ln(Yield)_{ij}$	-	+	-				-	-	+	

* *Yield is average fare price per mile (or per kilometre).*

As can be seen, the majority of existing airfare models reviewed above use average O-D fare as the dependent variable. Average fare (as well as all continuous explanatory variables) is commonly transformed into natural logarithmic form so that the coefficients can be interpreted as elasticities. In contrast, some models set the dependent variable as average yield, or average fare per passenger mile, which results in different signs in some coefficients. For instance, O-D distance, an explanatory variable that is included in almost all airfare models, is found to be positively correlated to average fare yet negatively correlated to average yield. According to these studies, O-D distance is used as a proxy variable for airline operating costs given that airline operating costs increase by O-D distance; hence the longer the distance, the higher the airfare. A major flaw of using proxy variables such as the O-D distance is that it can hardly capture changes in airline operating costs even if O-D distance is unchanged.

Airline operating costs consist of several categories, and some of the costs are relatively stable over time, such as aircraft maintenance cost, whereas others are fluctuating, such as airline fuel cost. Additionally, the proportion of each cost category to airline total operating costs varies significantly among different airlines and operating regional markets. As a result, an airline could potentially be more vulnerable to changes in one cost component than another. By not explicitly capturing the operating costs but using proxy variables in a pricing model makes it impossible to either reflect the effects of changes in one particular cost component to airfares or compare the cost effects on fares across different types of operating costs. The key challenge of including operating costs in these models is that, except for the U.S. Form 41 database (US DOT, 2017), no other country makes airlines' operating costs data available to the public at least at the airline-specific level (Belobaba, 2009).

From all the reviewed literatures in Table 2-1, airline competition is a research topic that has thus far received the most extensive discussion. Two factors are most commonly used to capture market competition, namely market concentration and the existence of low-cost carriers (LCC). The first factor, market concentration, measured by the Herfindahl-Hirschman Index (HHI)¹ in the previous literature, has been used to reflect airline's market structure (Borenstein, 1989; Brueckner, et al., 1992; Vowles, 2006; Hofer, et al., 2007; Zhang, et al., 2013). Higher market concentration indicates relatively low competition, and vice versa. From Table 2-1, market concentration is largely found to be positively correlated to airfares, which indicates that airlines tend to set higher airfares when there is less competition in the market. For example, Borenstein (1989) found that dominance of major routes and airports by one or two airlines results in up to 12 percent higher fares for passengers.

The other critical indicator of market competition is the presence of low-cost carriers (LCCs). A particularly sizable body of literature in this area has demonstrated a drastic downward pressure on fares driven by the LCC competition (Brueckner, et al., 1992; Dresner et al., 1996; Morrison, 2001; Goolsbee & Syverson, 2008; Cho, et al., 2012, Brueckner et al., 2013). Dresner et al. (1996) examined competitive impacts of Southwest's entry to the route-level fare prices. Their model results showed that the presence of LCCs resulted in an average of 38% lower fares at the route-level, and even more drastic fare reductions when Southwest serves the routes. Morrison (2001) found that the spill-over effects of Southwest Airlines serving one route can negatively affect fare prices of legacy carriers' service on the neighbouring route markets. More

¹ HHI is calculated as the sum of squared market shares of all competitors in a given market, where a market can be defined as either an itinerary or an airport. Hence, a larger HHI reflects higher market concentration and lower competition.

recently, using both weighted- and unweighted regressions, Brueckner et al. (2013) examined the impact of in-market (i.e. airport-pair) competition and adjacent competition between legacy carriers and LCCs. They found that the impact of LCC competition on airfares is substantial at both in-market airports (33% reduction in non-stop market and 12% reduction in connecting market) and adjacent airports. In addition, this study found a recent trend of legacy carrier competition in nonstop markets since 2000 (Brueckner et al., 2013).

Apart from the market competition variables, other factors are also found to affect airfares. As shown in Table 2-1, passenger demand could be either positively (Drenser et al, 1996; Hofer et al. 2007; Cho et al. 2002) or negatively (Brueckner et al., 1992; Vowles, 2006; Zhang et al., 2012; Zou & Hansen, 2014) correlated with fares. Specifically, as increased number of passengers represent higher levels of demand, it may lead to higher fares, known as the “demand” effect. In contrast, larger passenger numbers could also reflect routes with higher densities and lower costs, and thus result in lower airfares, known as the “economies of density” effects. The sign of demand variable depends on if the “demand” effect outweighs the “economies of density” effects.

Importantly, the simultaneity between airline demand and airfare raises the issue of endogeneity bias in many regression models. The endogeneity issue is caused because passenger demand, if included as an explanatory variable that partially determines airfares, is simultaneously determined by ticket prices. As a result, the traditional Ordinary Least Squares (OLS) approach is no longer appropriate in estimating such airfare models; instead, the endogenous variable (i.e. passenger demand) needs to be replaced by an instrumental variable (IV) and estimated using methods such as Two-stage Least Squares (TSLS) (Hofer et al. 2007; Zou & Hansen,

2014). Furthermore, load factor is another commonly used explanatory variable on airline pricing and is found largely to be negatively correlated to airfares, given that fewer passengers on a flight could result in higher ticket price being charged per passenger in order to cover airline operating costs. A few studies also find that flight frequency has statistically significant effects on prices. According to Chi and Koo (2009), higher flight frequencies could result in either higher or lower fares, depending on whether the effect of greater frequency on costs is larger than its effect on demand.

To conclude, although a number of determinants have been assessed in previous airfare models, the relationship between airline operating costs and airfares have rarely been explicitly explored. As mentioned earlier, in most cases proxy variables for operating costs, such as O-D distance, are used instead, to reflect the cost effects on airfares. Attempts also exist to use fuel price as proxy to airline fuel cost. Although fuel price data is publicly available, it can hardly capture the heterogeneity in airline fuel cost. This is because fuel cost is the product of fuel price and fuel burn, and annual total fuel burn could vary significantly across airlines, depending on their service network and aircraft portfolios. In short, these proxy variables cannot capture changes in airline costs, and thus are not useful to quantify how much of airlines' costs burden could be passed through onto passengers via higher airfares, known as airline's cost pass-through behaviour. This significant research gap prevents researchers from understanding to what extent airlines could adjust airfares in response to higher fuel cost resulted from the market-based environmental policies. Further, the uncertainty in airline pricing responses to MBMs would make it difficult to estimate how airline's demand and associated CO₂ emissions could be affected by the increased ticket prices.

2.1.3 Modelling airfares in the Aviation Integrated Model (AIM)

The Aviation Integrated Model (AIM), based at University College London (UCL), Energy Institute, is one of the leading aviation-environmental systems models that provide comprehensive analysis on environmental and economic interactions of aviation at local and global levels, now and into the future (Reynolds et. al. 2007). Consisting of seven interconnected modules, the AIM simulates cost and emissions of aircraft technology uptake, passenger demand, airline and airport activity, global climate impact, local environmental impacts such as air pollution and noise, and economic impacts of air transport both regionally and globally. However, airline pricing behaviour and changes of airfares resulting from cost changes are currently modelled in the AIM by a very simple cost-scaling approach: costs incurred by a global representative airline are fully passed onto passengers in form of higher fares, with a fixed rate of return. The approach, despite its simplicity and transparency, assumes airline costs as the only factor affecting airfares, and does not capture airline competition. It also fails to explicitly reflect the relationship between airfares and airline costs, where the rate of cost pass-through may parametrically vary by airline and by itinerary, taking into account market competition. Therefore, the development of a more rigorous airfare model that not only captures other key determinants (besides airline cost) of airfares but also explicitly reflects airline cost pass-through would add significant capability that is not yet addressed in any other air transport systems model.

2.2 Existing Research on Cost Pass-through

Previous section has concluded that as airline operating costs are rarely explicitly included in previous airfare models, the airline cost pass-through behaviour

is relatively unknown. This section firstly discusses the economic theory behind cost pass-through, and then presents a brief review of existing literature on the cost pass-through in industries that are well suited for such analysis. Following that, it reviews previous approach to reflect the potential airfare changes under MBMs for aviation emissions reduction. This section concludes by a discussion on key challenges of assessing cost pass-through in the air transport sector.

2.2.1 Economic theory of cost pass-through

Cost pass-through is defined as changes in prices of products or services following a change in their costs (RBB Economics, 2014). When the changes are measured in cent-by-cent terms, it is known as the absolute cost pass-through rate; on the other hand, when the changes are measured in percentage terms, it represents the cost pass-through elasticity (RBB Economics, 2014).

Both theoretical and empirical literatures on cost pass-through indicate that the extent of cost pass-through may vary substantially from one setting to another, depending on the market structure and competition, i.e. the number of active competitors (N) in the market, the shape of the demand curve, and the shape of the supply curve. The market structure is either monopolistic ($N=1$), duopolistic ($N=2$), oligopolistic ($N = \text{small}$), or competitive ($N = \text{large}$). RBB Economics (2014) and Sijm et al. (2008) provided comprehensive reviews on the economic theory of cost pass-through based on various market conditions. To put this discussion into the context of the air transport sector, possible pass-through rates to airfares under different market structures are discussed next.

Under perfect competition, airfares are equal to marginal costs (Zimmerman & Carlson, 2010; Koopmans & Lieshout, 2016; Sijm et al., 2008). The burden of

increased cost is split between airlines and passengers, and the proportion that each group ends up paying depends on the relative elasticities of supply and demand (Pindyck & Rubinfeld, 2013). Specifically, the more elastic is demand compared to supply, the smaller the extent of cost pass-through, all else being equal (RBB Economics, 2014). In contrast, if demand is highly elastic relative to supply, airlines will have to absorb the cost increase by themselves, with little increases in airfares. Notably, regardless what fraction of the cost that airlines and passengers will have to pay, there is always a deadweight loss of total surplus of both groups (Pindyck & Rubinfeld, 2013).

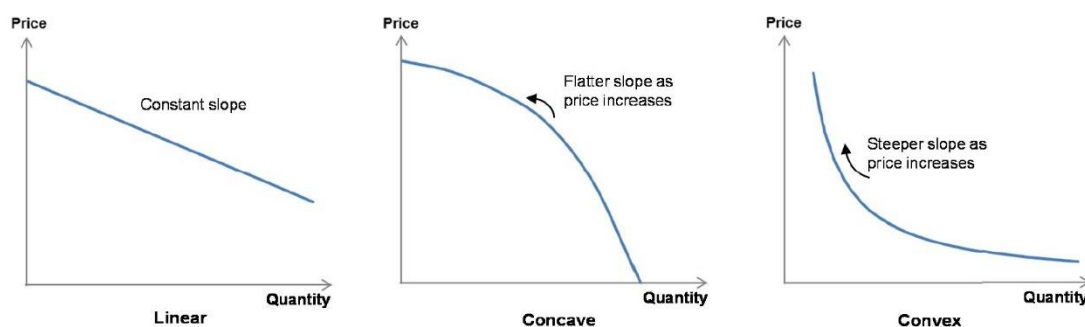


Figure 2-1. Curvature of the demand curve (Source: RBB Economics, 2014).

In comparison, under other market structures, especially a monopolistic market, price exceeds marginal cost, and the cost pass-through depends entirely on the shape of the demand curve (RBB Economics, 2014; Pindyck & Rubinfeld, 2013). As Figure 2-1 shows, if the demand curve is linear with constant slope, the rate at which demand drops as price increase never changes (RBB Economics, 2014). Thus, the more elastic the demand (i.e. the flatter slope the linear demand is), the lower rates of cost pass-through are expected (e.g. pass-through rate is zero if demand is perfectly elastic). On the other hand, if the demand curve is concave, i.e. slope becomes flatter as price increases, it means that passengers are more price sensitive as price goes up. Hence, a full cost pass-through to airfares would result in a lot reduction in passenger demand,

making a higher pass-through rate less attractive to airlines. In contrast, a convex demand curve where slope becomes steeper as price increases suggests that when price goes up, remaining demand becomes less price sensitive. Thus, pass-through rate is higher (possibly greater than 100%) with convex demand.

In the oligopolistic market where only a few airlines account for most or all of market shares, these airlines can make substantial profits by just maintaining their market shares. It is often the case that the airline with the largest market share sets quantities of price rise in response to the cost increase, and others almost follow its lead to make sure their profits not badly affected by rocking the boat (Pindyck & Rubinfeld, 2013; Koopmans & Lieshout, 2016). Therefore, similar to the case in the monopolistic market, cost pass-through rate in the oligopolistic market is also determined by the elasticity of demand, or the shape of the demand curve.

Relatedly, the shape of the supply (marginal cost) curve also has an effect on cost pass-through. Although much of the theoretical literature considers marginal cost as being constant, i.e. a flat, horizontal line (RBB Economics, 2014; Sijm et al. 2008), it is expected that for the airline industry, the supply curve has an upward slope, which indicates that marginal cost increases as output increases. Compared to a constant marginal cost, an upward sloping marginal cost will lead to lower cost pass-through, because increase in price due to cost pass-through will result in a decrease in output and thereby a decrease in other components of marginal costs. Therefore, this mitigates (part of) the cost-raising effect of the cost shock (RBB Economics, 2014).

Although the economic theory behind cost pass-through is well understood, it is found in the next section that the empirical literature on cost pass-through is unbalanced in which the cost pass-through in air transport industry has been rarely explored.

2.2.2 Cost pass-through analysis in existing literature

2.2.2.1 *The mainstream of previous cost pass-through research*

Given that cost pass-through measures how changes in costs lead to changes in price, the cost pass-through analysis has been conducted extensively in previous literature for industries that have large volume of disaggregated, high-frequency time-series data on both cost and price. For example, there is a vast empirical literature on the pass-through of international crude oil shocks to domestic retail fuel prices (Radchenko, 2005; Grasso & Manera, 2007; Honarvar, 2009; Meyler, 2009; Coady et al., 2010; Clements et al. 2013; Kpodar & Abdallah, 2017). In addition, the empirical literature on the pass-through of exchange rate is also extensive, particularly for the automobile industry (Gron & Swenson, 2006), the import prices (Campa & Goldberg, 2005; Jimborean, 2013), and the coffee industry (Gomez & Koerner, 2002; Frey & Manera, 2005; Aguiar & Santana, 2002; and Leibtag et al. 2007).

Kpodar and Abdallah (2017) estimated the pass-through of crude oil prices on retail fuel prices for gasoline, diesel, kerosene, and Liquefied Petroleum Gas (LPG), using a monthly dataset of retail fuel prices in 162 countries over the period from January 2000 to December 2014. Measuring pass-through as absolute changes in prices, they concluded that, on average, a one cent increase in crude oil prices per litre translates into a 0.7 cent increase in the retail gasoline price per litre within three months after the crude oil shock. Relatedly, Meyler (2009) assessed the pass through of global crude oil prices into consumer liquid fuel prices in the euro area, using both absolute pass-through and percentage pass-through measures. From his estimation, increases in oil prices are fully passed through to consumer fuel prices in a cent-by-cent measure, whilst if using logarithmic transformations, the estimated percentage

pass-through is higher due to a substantially increased share of oil prices that is related to the consumer fuel price during 1994 to 2008.

More recently, a growing number of studies has focused on the pass-through of carbon cost to electricity prices, given the introduction of the EU Emissions Trading Scheme (ETS) (Sijm et al. 2006; Bunn & Fezzi, 2007; Sijm et al. 2008; Kim et al. 2010; Fabra & Reguant, 2013). Although at the early phase of the EU ETS, power companies received the ETS allowances for free, it is found that the opportunity costs of CO₂ emissions allowances were still passed through to the power prices. Sijm et al (2006) estimated that, depending on the carbon intensity of the marginal production unit and various technology-specific factors, power companies in Germany and Netherlands pass through about 60-100% of the CO₂ cost to electricity prices. One important difference between the pass-through of oil price to retail fuel prices discussed earlier and the pass-through of CO₂ cost to electricity prices is that, unlike changes in retail fuel prices which are almost exclusively affected by changes in crude oil prices, changes in electricity prices under the EU ETS are determined by changes in at least two cost components, i.e. the fuel cost and the CO₂ cost, both depending on specific energy sources used by power plants. Therefore, variations of the electricity prices need to be explained by the variations in both the fuel cost and the CO₂ cost, assuming other operational and maintenance costs are constant (Sijm et al. 2006). This case is very similar to airline cost pass-through, where changes in airfares may be affected by changes in multiple airline operating cost components.

With this setting, Sijm et al. (2006) specified the pass-through regression as:

$$P_t = \alpha + \beta_1 CO2_t^{c,g} + \beta_2 F_t^{c,g} + \varepsilon_t \quad (2-1)$$

where $CO2_t^{c,g}$ is the CO₂ cost associated with coal and gas at time t , and $F_t^{c,g}$ is the fuel cost of power generation by coal and gas at time t . To estimate the CO₂ cost pass-

through only, they assume that the fuel cost is fully passed on to power prices, which is equivalent to fixing the coefficient β_2 at unity. As such, Y_t as the difference between power price and fuel cost represents the CO₂ cost part of the power price, and the coefficient β_1 is the CO₂ cost pass-through rates to be estimated.

$$Y_t = (P_t - F_t^{c,g}) = \alpha + \beta_1 CO2_t^{c,g} + \varepsilon_t \quad (2-2)$$

Sijm et al. (2008) expanded this study by assessing the CO₂ cost pass-through in both wholesale and retail power markets in France, Germany, Sweden, Netherlands, and UK, and found that cost of emissions allowances is passed through to power prices in all these countries, resulting in higher electricity prices for consumers and additional ('windfall') profits for power producers.

2.2.2.2 Other related topics in previous cost pass-through studies

In the cost pass-through literature, a phenomenon that in response to cost changes, prices rise more strongly or quickly than they fall is a much-discussed issue (Ritz, 2015). To assess the asymmetric pass-through, a common method is to differentiate between the effects of positive and negative cost changes on price and then investigate whether prices respond similarly when cost rise or fall through comparing the associated pass-through coefficients (Ritz, 2015). Asymmetric pricing response has been found in many sectors (Peltzman, 2000). For example, Enders and Granger (1998) on the term structure of interest rates, Goodwin and Holt (1999) in the U.S. beef industry, Toolsema and Jacobs (2007) on mortgage rates, Zachmann and von Hirschhausen (2008) on wholesale electricity prices, and Kpodar and Abdallah (2017) on asymmetric pass-through of crude oil price in retail gasoline markets.

There are also a few studies specifically assessing the asymmetric response in the airline industry. Wadud (2015) found evidence that airfares increase quicker when

fuel prices increases but fall slower in response to a reduction in fuel prices. In an earlier work, he also demonstrated imperfectly reversible aviation demand responses to fuel price and income changes, while acknowledging the possibility that demand could be perfectly reversible and it is the asymmetric pricing response to fuel prices that causes the imperfectly reversible demand (Wadud, 2014). Escobari (2013) using a unique daily time-series data found that falling capacity cost due to demand fluctuations has no effects on fares whilst increases in the cost are passed on to fares.

Heterogeneity has also been discussed extensively in the cost pass-through literature (RBB Economics, 2014; Neuhoff & Ritz, 2019; Grey & Ritz, 2018). As an example of heterogenous cost past-through in the airline sector, Grey and Ritz (2018) conducted a comprehensive study comparing the firm-level cost pass-through between LCC (Southwest Airline) and legacy carriers in the domestic US market. They found that there is a large inter-firm heterogeneity in fuel cost pass-through, even for a uniform fuel cost shock. Southwest is found to pass-through increased cost by more than 100% (1.48 ± 0.08) while the pass-through of legacy carriers is significantly below 100% (0.55 ± 0.12). Based on their analysis, the pass-through heterogeneity could be explained 62% by different route portfolios where legacy carriers tend to fly longer routes with lower pass-through, 26% by Southwest using more fuel-efficient aircraft on the same routes, and the remaining 12% by the differences in customer demand (Grey & Ritz, 2018).

2.2.3 Previous approach to address airline cost pass-through

As described in Chapter 1, the market-based measures (MBMs) that aim to mitigate CO₂ emissions of aviation will effectively increase airline fuel cost. When evaluating how the increased fuel cost could contribute to emissions reduction from

airlines, an important question is to what extent airlines are able to pass through the cost increases to airfares. Unfortunately, there is little empirical evidence of cost pass-through available for the aviation industry at a global scale. PWC (2005), using a simple regression model, concluded that airlines in the UK market pass on 90-105% of the increase in kerosene costs to passengers through airfares; however, this study did not control for other important factors on airfares such as market competition. Using a panel data of 18 European airlines from 1990 to 2007, Toru (2011) examined increases in fuel prices resulting from the EU Emissions Trading Schemes (EU ETS) and found that the level of cost pass-through is close to 100%, but only when the higher fuel prices triggered reductions in airline seat capacity.

The majority of existing research assessing the MBM effects on aviation emissions, however, have relied on pre-assumed cost pass-through based on their assumptions on market structure. With the pre-assumed cost pass-through, literature in this area mainly examined the impacts of the EU ETS on air transport demand (Lu, 2009; Hofer et al, 2010; Miyoshi, 2014), airline operations (Brueckner & Zhang, 2010; Albers et al., 2009), and airline competition (Scheelhaase & Grimme, 2007; Scheelhaase et al, 2010; Barbot et al., 2014; Meleo, 2014; Meleo et al., 2016).

Lu (2009) found that under full cost pass-through, low-cost carriers serving intra-European short-haul routes lose more passengers than legacy carriers because LCCs are more sensitive to additional cost. Under two scenarios of cost pass-through, i.e. 35% and 100%, Albers et al. (2009) concluded that because of the EU ETS, the airline cost increase will range from €9 to €27 per route with a carbon price of €27/tCO₂, and this will result in a moderate fare increase. Using a theoretical model for competing duopoly airlines, Brueckner and Zhang (2010) concluded that emission charges will increase airfares, reduce flight frequency, increase load factors, and

improve aircraft fuel efficiency. In a study of the EU ETS impacts on the Italian airline market, Meleo (2014) and Meleo et al. (2016) addressed the cost pass-through effects by having three scenarios: 0% pass-through, 50% pass-through, and 100% pass-through, and found that very limited emissions-costs effect on fares due to a low level of carbon prices (at €7.1, €15, and €25/tCO₂), i.e. price increases stay under 1% in 2013, 2014, and 2015, respectively, even for the scenario of 100% cost pass-through.

Instead of assuming a fixed cost pass-through rate, a few studies have also attempted to model the rates of cost pass-through. Girardet and Spinler (2013) calculated the percentage of price change in kerosene and CO₂ emissions that is passed onto passengers using a dynamic profit optimization model. Fluctuation of prices for kerosene and CO₂ emissions are included, but in a monopolistic price setting where no market competition is considered. Pagoni and Pasarakis-Kalouptsi (2016) computed the cost pass-through rates by jointly estimating a demand and supply model, taking into account a number of factors such as market structure and level of competition. Demand is estimated by a discrete choice model using market-level data, and airline supply is estimated using a linear model. The post-policy fares are determined from the new equilibrium in demand and supply. This approach has a distinct advantage over previous approaches because it captures airfare adjustments based on supply and demand rather than the pre-specified cost pass-through rates. However, the estimated cost pass-through rates are still model-based and provide limited empirical insights. Lastly, like other previous research, it focused solely on the domestic U.S. airline market, which in reality does not implement a market-based aviation emissions policy yet.

As reviewed above, due to the lack of the empirical evidence on airlines' cost pass-through behaviour, previous studies have largely relied on either the pre-assumed

rates of cost pass-through or the model-based estimation approach. As a result, there are significant uncertainties in previous research findings on how airlines would respond to the market-based emissions reduction policies. A solid empirical assessment on airline cost pass-through is at the heart of a better understanding to this issue. In addition, the potential cost pass-through effects need to be evaluated across different airline markets, as airlines may cross-subsidise costs based on different price sensitivities in these markets. To fill this research gap, an airline pricing model that has the capability of capturing airline operating costs and explicitly reflecting the relationship between airfares and various operating costs would be required. However, such efforts are under-explored because of the challenges in data availability.

2.2.4 Key challenges in assessing airline cost pass-through

Due to a shortage of suitable data, quantifying cost pass-through in the air transport sector is considerably more challenging than for the industries discussed in Section 2.2.2. Econometric methods often measure cost pass-through by estimating a statistical relationship between cost and price variation, which seek to identify how price changes could be explained by cost changes, after controlling for other potential confounding influences on price (RBB Economics, 2014). Pass-through estimation in general requires high-frequency time-series data on price and cost for all firms operating in a product market (Neuhoff & Ritz, 2019). However, for the airline industry, obtaining relatively high frequency (e.g. monthly) time series data on both airline cost and airfares with a global coverage is very challenging.

The most detailed price data with public access come from the U.S. DOT DB1A/B Origin and Destination Survey, a 10% sample of all airline tickets sold (DOT, 2019). However, this data have a narrow coverage for only the domestic U.S. airline

market. Time-series data of airfares beyond the U.S. market could be collected from airline ticket booking websites whilst it is practically impossible for researchers to collect such data for all airlines and itineraries at the global scale. Purchasing such data from commercial databases is possible but could be extremely costly. On the other hand, obtaining airline cost data is even more difficult. In fact, the only publicly available cost data of passenger air travel is reported by the U.S. DOT Form 41 database (DOT, 2019) and again is only for major U.S. airlines. According to Belobaba (2010), no other country except for the U.S. makes available such detailed operating cost data to the public. Therefore, the lack of comprehensive and high frequency time series and cross-country data on fare prices and airline costs is perhaps a the most important reason that there is to date very limited empirical evidence with respect to the cost pass-through in passenger air travel, compared to other sectors.

Nevertheless, attempts could be made to estimate cost pass-through using cross-sectional airline data, which is relatively easier to obtain from commercial databases. Although cross-sectional data cannot reflect temporal variations in prices, it does contain spatial variations in prices due to regional differences and quality effects, which could be matched to the spatial variations in costs for estimating the cost pass-through elasticities. In fact, there has been extensive discussions in the literature on the feasibility of estimating elasticities from cross-sectional data (Cox & Wohlgemant, 1986; Deaton, 1988; Perali & Chavas, 2000; Yen et al., 2003). Prais and Houthakker (1955) argued that price variations exist in cross-sectional data due to regional differences, price discrimination, differences in level of services provided, and quality variations. Further, Friedman (1976) suggested that estimating elasticities from spatial data is essentially the same from time-series data when conditions of supply vary considerably, while conditions of demand vary little. Friedman's

condition is well-suited for the air transport markets, where different O-D markets have distinct supply conditions, i.e. total operating costs often vary significantly between non-stop and connecting itineraries that connect the same O-D markets, because costs are principally determined by flight distances, the type and age of aircraft used, and the proportion of seats filled, etc., in the meantime, airfares on these itineraries also vary considerably.

Still, it is important to distinguish between elasticities estimated on cross-sectional data and time-series data. In transport demand modelling literature, cross-sectional data is mostly used for short-run demand analysis, based on regional statistics at an aggregate level or using Stated-Preference (SP) Survey data or combined SP and Reveal-Preference (RP) Survey data to retrieve individual information (Tsai et al, 2014; Douglas et al., 2003; Hensher, 1998; Hensher & King, 1998). On the other hand, time-series data is used to analyse long-run demand, as it can capture the lagged behavioural adjustments of travellers given system changes of public transport. This is known as the “temporal effect” of travel behaviour (Tsai et al. 2014). Without reflecting long-run behaviour changes due to the unavailability of the temporal dimension in the data, demand models based on cross-sectional data only provide the short-run elasticities. Results from previous research have shown that long-run demand elasticities are greater than short-run demand elasticities, because travellers have more options to change their travel behaviour in the long run as compared to the short run (Oum et al. 1992; Bresson et al., 2003; Dargay et al., 2010; Dargay & Hanly, 2002; Graham et al., 2009; Voith, 1991). Hence, as Litman (2004) pointed out, conventional travel demand models based on short-run elasticities may underestimate the long-term impacts of service changes on public transport ridership.

Linked to this, cost pass-through elasticities estimated based on cross-sectional data are the short-run elasticities. Thus, these elasticities are likely to be lower than the cost pass-through elasticities estimated on the high-frequency time-series data. An implication of using short-run cost pass-through elasticities in estimating the possible effects of MBMs on aviation is that airfares may increase less than it could have in the long run, after an increase in airline fuel cost. As a result, the associated reductions in both aviation demand and CO₂ emissions might also be underestimated, depending on the price elasticity of demand in a given airline market.

2.3 High-Speed Rail Mode Substitution for Air Transport

As described in Chapter 1, since the dependence of transportation on petroleum-based fuels varies across different modes, mitigation strategies that encourage modal shift from energy-intensive modes to a relatively “green” alternative could potentially contribute to energy savings and emissions reduction from passenger transport. In this section, a brief overview of the fundamental relationships between transport activities, energy use, and CO₂ emissions is firstly presented, with an emphasis on the determining role of energy intensities of air transport and HSR in their environmental performances. Following that, a review of existing studies on the competition and substitution effects of HSR for air transport is presented.

2.3.1 Energy use and CO₂ emissions from passenger transport

Due to its large scale and strong oil dependence, passenger transport has strong implications for global energy consumption and climate change. This section reviews the fundamental relationship that connects passenger transport with energy consumption and CO₂ emissions.

In transportation, energy is required to move passengers and goods by different types of vehicles over certain distances. Such energy can be provided in various forms depending on the mode of transport. For example, motor gasoline is the dominate fuel for passenger cars; rail transport can be powered by electricity, diesel, or coal; and air transport mainly relies on petroleum-based jet fuels. For all these transport modes, the total energy consumption can be calculated as (IEA, 2016):

$$\text{Energy Consumption} = \text{Transport Activities} \times \text{Energy Intensity} \quad (2-3)$$

According to IEA (2017b), transport activity is commonly measured by passenger-kilometre-travelled (PKT), where one PKT represents transporting one passenger over one kilometre; and energy intensity² (EI), i.e. energy use per PKT, indicates the amount of energy used to move one passenger over one kilometre. From Eq.(2-3), it can be seen that with transport activities being equal, the energy use of different transport modes depends on their specific energy intensity.

There are a number of factors that may affect the energy intensity of a given transport mode. Taking light-duty vehicle (LDV) in the United States as a case study, Schäfer et al. (2009) discussed contributing factors to the changes in LDV energy intensities during the period of 1970-2005. They concluded that, overall, a decline by about 0.3 mega-joules (MJ) per PKT in LDV energy intensity over this time period was a result of a 1.2 MJ/PKT energy intensity drop from LDV fuel consumption reductions, offset by an increase in energy intensity of 0.7 MJ/PKT caused by a declining occupancy rate and by another increase of nearly 0.2 MJ/PKT due to a shift from automobiles to light trucks. Therefore, energy intensity of a transport mode is a result of complicated interactions between underlying determinants. As Schäfer et al.

² Often, energy intensity is presented not per PKT but per VKT (vehicle-kilometre-travelled) or per seat-kilometre. PKT = VKT × average occupancy rate (PKT/VKT) of the vehicle; and VKT = per seat-kilometre × total number of seats on the vehicle.

(2009) stressed, reducing energy intensity in the transportation sector relies on technological improvements, fuel efficiency gains, and modal shift from energy-intensive modes to less energy-intensive modes. However, such efforts may be offset by non-technology-related factors such as people's preference to faster, larger, and thus more energy-intensive vehicles, and increasing urban driving, etc.

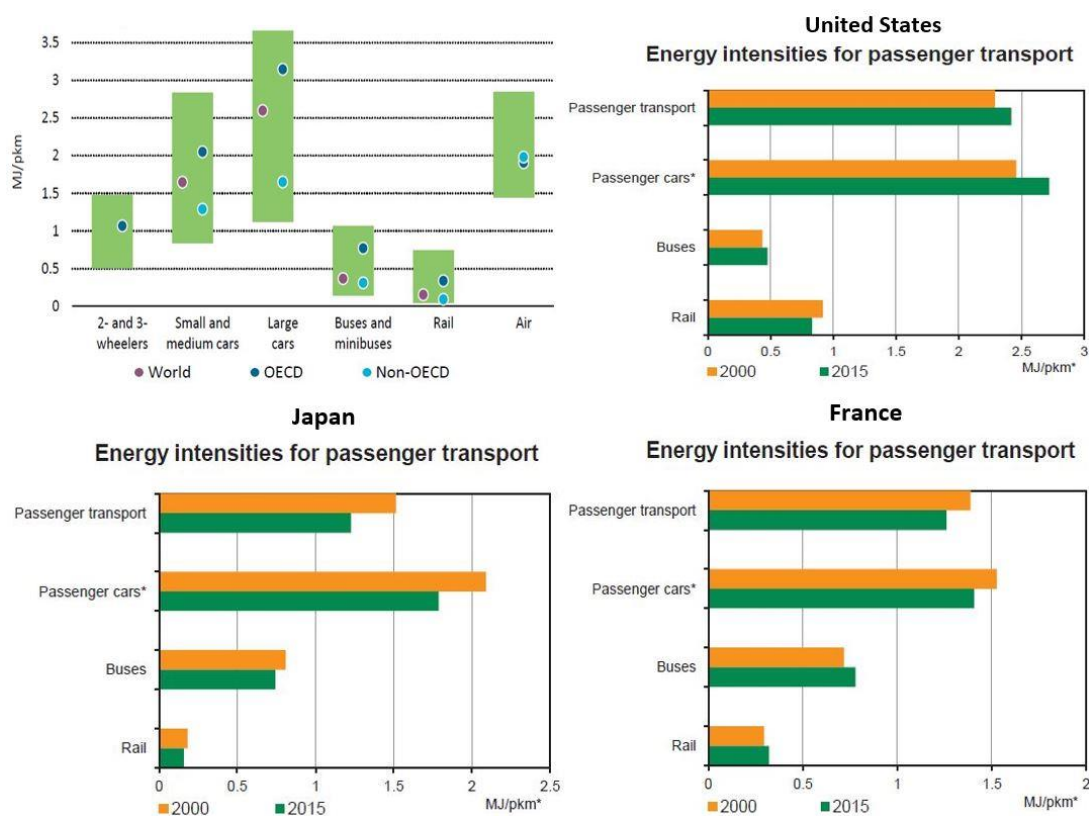


Figure 2-2. Energy intensities for passenger transport in selected countries (source: IEA, 2016; 2017b).

Figure 2-2 shows energy intensity of different modes of transport in selected countries. The upper left panel in Figure 2-2 shows energy intensity of different passenger transport modes of the world average, the OECD countries, and the non-OECD countries, respectively. As can be seen, air transport and passenger cars (small to large sizes) are more energy intensive than public road transport and rail. However, variations in energy intensities of air transport between the OECD and the non-OECD countries are the smallest at about 2 MJ/pkm.

Figure 2-2 also depicts energy intensities of passenger transport in the United States, Japan, and France, as an example of variations in transport energy intensity in different countries. As can be seen, the average energy intensity of passenger transport was particularly high in the United States at almost 2.5 MJ/pkm in 2015. This is mainly driven by the use of large passenger cars (with an average energy intensity at about 2.7 MJ/pkm). In contrast, Japan and France had smaller energy intensities in the passenger transport sector, both around 1.25 MJ/pkm in 2015. This is almost 50% lower than the U.S. Importantly, rail is one of the least energy intensive modes in both countries, which happened to have are the world's second (Japan) and fourth (France) largest high-speed rail (HSR) networks by the end of 2015 (UIC, 2016).

Because of the remarkably low energy intensity of rail systems, this mode of transport, which accounted for almost 32% of the Japan's total domestic transport demand, consumed only 2.4% of the country's final transport energy use in 2015 (IEA, 2016; UIC, 2018). This suggests that, if rail could become an attractive alternative for high-speed intercity travel, it has the potential to contribute significantly to reducing energy consumption in the transport sector due to its high energy efficiency compared to modes such as aircraft or passenger cars.

Having reviewed how transportation is connected to energy consumption with an emphasis on the importance of energy intensity in determining the final energy use of a transport mode, I now discuss how transportation energy is translated into CO₂ emissions. The estimation of CO₂ emissions from fuel combustion for a given fuel is given in Eq.(2-4) (IEA, 2017c), and is mainly determined by the emission factor (gCO₂/MJ) of a specific fuel:

$$\text{CO}_2 = \text{Fuel consumption} \times \text{Emission factor} \quad (2-4)$$

For transport modes that consume electricity instead of directly combusting fuels, emissions mainly result from generating electricity at power plants. Thus, CO₂ emissions are calculated based on the emissions factor from power generation, known as the carbon intensity of power generation, as shown in Eq.(2-5) and Eq.(2-6):

$$\text{CO}_{2\text{electricity}} = \text{Electricity consumption} \times \text{CO}_2/\text{kWh from Electricity Gen} \quad (2-5)$$

Eq.(2-5) uses the average CO₂ per kilowatt hour (kWh) from electricity generation. Given that electricity can be generated by numerous sources, including coal, oil, natural gas, and renewables, etc., a slightly different approach is to account for emissions factors of specific energy sources and their shares in power generation mix as shown in Eq.(2-6):

$$\text{CO}_{2\text{electricity}} = \sum_i \{ (\text{CO}_2/\text{kWh})_i \times \frac{\text{Elect.Gen}_i}{\text{Elect.Gen}} \times \text{Electricity consumption} \} \quad (2-6)$$

From Eq.(2-6) it can be seen more explicitly that the electricity mix plays a critical role in determining the final CO₂ emissions of an electrified transport mode: given that both the carbon intensity (gCO₂/kWh) and the share of electricity generated from source *i* varies country by country, it would not be surprising if an electrified transport produces more emissions in one country than it does in a different country. In fact, previous study by Moro and Lonza (2017) showed that electric vehicles in countries with highly carbon-intensive electricity mix such as Latvia, are associated with more CO₂ emissions (169-234 gCO₂eq/km) than diesel-fuelled cars (145 gCO₂eq/km).

2.3.2 Energy and CO₂ emissions: Air Transport vs. HSR

Having discussed the general relationship between transport activities, energy use, and CO₂ emissions from transportation, now I focus on a comparison between air

transport and high-speed rail (HSR). Recall from Figure 2-2 that rail is the one of the most energy efficient modes of transport whereas air transport is one of the most energy intensive modes. However, HSR as an advanced rail system is not assessed in IEA's (2017b) report. Thus, this section specifically compares the energy intensities of air transport and HSR from the existing literature.

Air Transport Energy Intensity

Based on historical data of the U.S. airlines, Lee et al. (2001) summarized the evolution of energy intensity by individual aircraft and year of introduction and provided projections for future aircraft energy intensity, as shown in Figure 2-3.

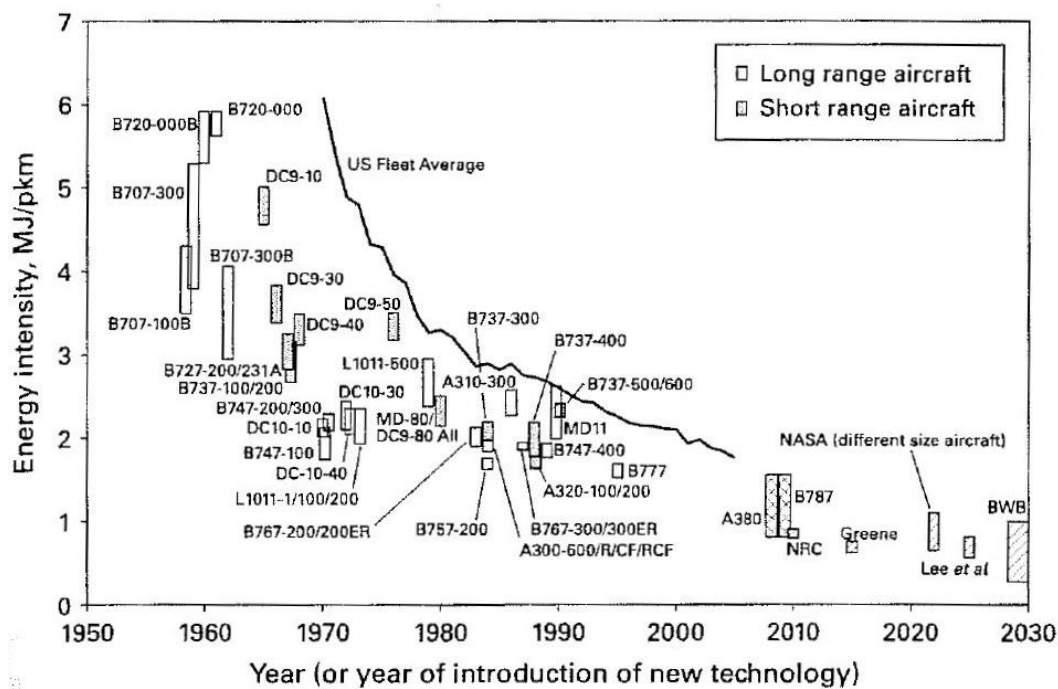


Figure 2-3. Evolution of aircraft energy intensity and future projections based on historical data for US airlines (source: Lee et al, 2001).

Compared to other passenger transport modes, air transport has experienced a much stronger decline in energy intensity, by about 70% between 1970 and 2005 (Schäfer, et al., 2009). Such remarkable reduction in energy use was achieved mainly through improvement in engine design, but also attributed to other factors including higher load factors, increased aircraft size, and operational improvements. Due to

different operating conditions, variations in energy intensity for each aircraft type can be significant by up to 30 percent, represented by the vertical extent of the small bars in the figure. Nevertheless, the strong historical decline in energy intensity is manifest, dropping from 6 MJ/pkm in 1970 to about 1 MJ/pkm at the lower bound of A380 and B787 in 2010. The U.S. BTS (2019) reports the historical average energy intensity of different passenger transport modes. In 2015, domestic air transport in the U.S. had an average energy intensity of 2,298 Btu per passenger-mile (equivalent to 1.51 MJ/pkm), and average energy intensity of international flights origin from or arriving to U.S. was 3,248 Btu per passenger-mile (equivalent to 2.13 MJ/pkm).

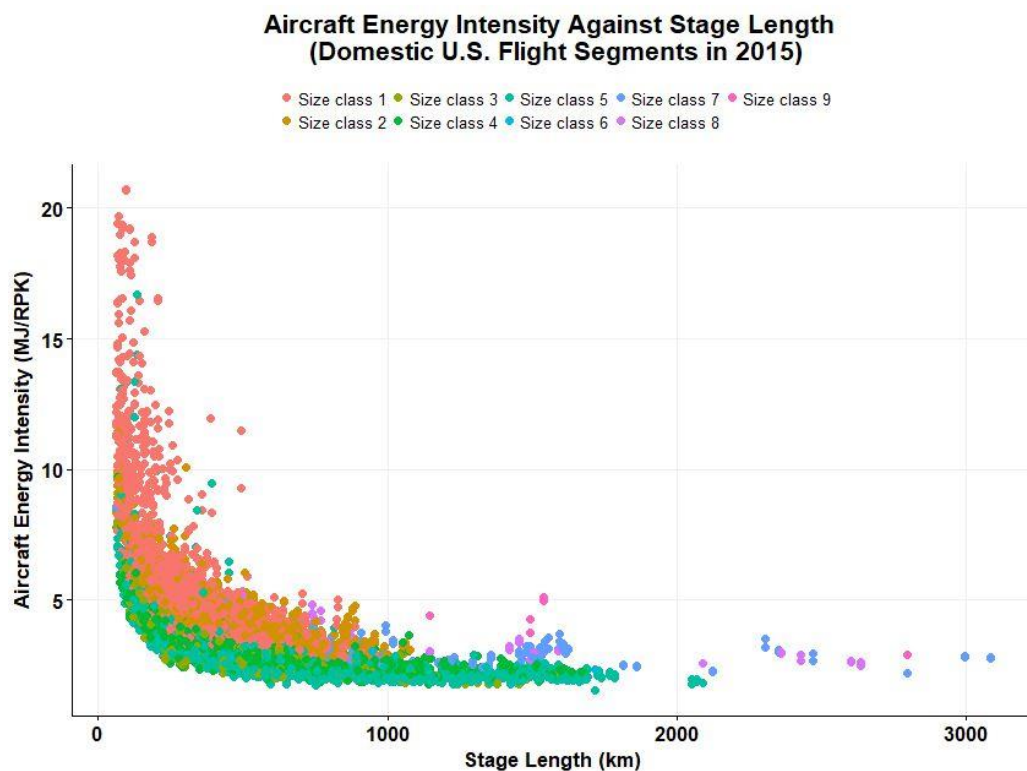


Figure 2-4. Aircraft energy intensity by aircraft size over stage length, U.S. domestic segments 2015.

Moreover, aircraft energy intensity strongly depends on stage length, which is much higher over shorter distances. Therefore, it is more useful to examine energy intensity of aviation by aircraft type and by stage length. As an illustration, I estimated the energy intensities of all flight segments in the domestic U.S. airline market in 2015,

using the Form 41 T100 domestic segment data (BTS, 2019) and the PIANO-X aircraft performance model (Lissys Ltd, 2017). Figure 2-4 depicts energy intensity of aircraft over stage length of the U.S. domestic segments in 2015. Aircraft are grouped into nine size classes based on number of seats and maximum take-off weight (MTOW) of an aircraft (Sustainable Aviation, 2015, see Appendix A). Aircraft size increases from class 1, which represents small regional jet such as CRJ 700, to class 9 represented by very large aircraft such as Airbus A380-800.

As can be seen, energy intensity could vary almost tenfold over stage length. The energy intensity on very short-distance segments, where small regional jets (size class 1) are largely adopted, can be as high as 20 MJ/pkm. The energy intensity drops significantly at a stage length between 100km and 400 km and then declines gradually as distance increases. Notably, energy intensity of large aircraft (size class 7-9) could also be relatively high, shown as the small peak of a few data points at about 1500 km. This is a result of low load factor on these aircraft which lead to higher energy use per passenger-kilometre.

HSR Energy Intensity

Similar to all electrified transportation modes, energy consumption of HSR operation is a function of HSR train's electricity intensity, i.e. the amount of electricity consumed by HSR per PKT (or per VKT, per seat-kilometre, etc.). A literature survey was conducted on the key parameters (or assumptions) of HSR vehicles, including electricity intensity, seat capacity, and average load factors, etc. The findings of the literature survey are summarised in Table 2-2. Although the survey covers HSR routes in different countries, in some studies the reported electricity intensities remain uncertain and may not reflect the real electricity use. This is mainly because actual electricity consumption data by HSR line is, if not impossible, challenging to obtain.

Table 2-2. Literature survey on previous studies of HSR energy consumption.

Study	Region	Corridor	Distance (km)	Vehicle	Seats	Load Factor	Electricity Intensity	Electricity Intensity (MJ/pkm)	Carbon Intensity of Electricity Generation	CO ₂ emissions from HSR operation	CO ₂ emissions from aircraft operation
Baron, et al. (2011)	France	Tours-Bordeaux	302	TGV Duplex & Reseaux	551	70%	24.1 kWh/train-km	0.23 MJ/pkm	91 gCO ₂ /kWh	5.7 gCO ₂ /pkm	N/A
		Valence-Marseille	250					0.23 MJ/pkm	91 gCO ₂ /kWh	5.7 gCO ₂ /pkm	163.2 gCO ₂ /pkm
	Taiwan	Taipei-Kaohsiung	345	THSR 700T	989	46%		0.19 MJ/pkm	747 gCO ₂ /kWh	42.9 gCO ₂ /pkm	N/A
	China	Beijing-Tianjin	117	CRH3	556	70%		0.23 MJ/pkm	865 gCO ₂ /kWh	39.2 gCO ₂ /pkm	N/A
Clewlow (2012)	U.S.	California HSR	1300	CAHSR	900	25-50%	74.2 kWh/train-mile	0.37-0.74 MJ/pkm	Reference case Cap-and-trade Clean energy	8-47 gCO ₂ /p-mile	213-344 gCO ₂ /pax-mile
		Northeast Corridor	735							19-221 gCO ₂ /pax-mile	234-446 gCO ₂ /pax-mile
Chester & Horvath (2012)	U.S.	California HSR	900	CAHSR	1200	25-110%	171.3kWh/train-mile	0.29-1.28 MJ/pkm	290 gCO ₂ /kWh (California) 560 gCO ₂ /kWh (Massachusetts)	95 gCO ₂ /train-mile 123 gCO ₂ /train-mile	230 gCO ₂ /pax-mile (Embraer 145) 170 gCO ₂ /pax-mile (B737) 150 gCO ₂ /pax-mile (B747)
Alvarez (2010)	Spain	Madrid-Barcelona	620	AVE	397	70%	0.09 kWh/pkm	0.32 MJ/pkm	240 gCO ₂ /kWh	28.4 gCO ₂ /pkm	145.86 gCO ₂ /pkm
		Madrid-Seville	396							23.7 gCO ₂ /pkm	N/A
Miyoshi & Givoni (2013)	UK	London-Manchester	331	Alstom AGV	550	60%	0.033 kWh/seat-km	0.20 MJ/pkm	300-500 gCO ₂ /kWh	30.5-45.7 gCO ₂ /pkm	N/A
Von Rozycki et al. (2003)	Germany	Hanover-Wuerzburg	325	ICE1 and ICE2	669	46%	22.5 kWh/train-km	0.26 MJ/pkm	647 gCO ₂ /kWh	69.4 gCO ₂ /pkm	N/A
Kato et al. (2005);	Japan	Tokyo- Shin Osaka	515	Shinkansen	1323	65%	0.029 kWh/pkm	0.10 MJ/pkm	422 gCO ₂ /kWh	3.9 gCO ₂ /pkm	34 gCO ₂ /pkm
Taniguchi (1992)		Tokyo-Morioka	496		731	70%	0.037 kWh/pkm	0.13 MJ/pkm	454 gCO ₂ /kWh	4.2 gCO ₂ /pkm	N/A
Lee et al. (2008)	South Korea	Seoul-Busan	412	KTX	935	65%	0.067 kWh/pkm	0.24 MJ/pkm	546 gCO ₂ /kWh	29.4 gCO ₂ /pkm	N/A

Apart from the electricity intensities summarized in my review, Chester and Horvath (2012, supplementary document Table S2) also provide a range of electricity intensity values for different HSR vehicles. My literature survey enhances their work by providing additional information with respect to the seat capacity of HSR, assumptions on average occupancy rates, and the carbon intensity of electricity mix. These parameters are all critical in estimating the final electricity consumption and CO₂ emissions from HSR. All the information as shown in Table 2-2 enables me to compare not only the energy intensity of air transport and HSR but also the contributing factors that determines the emissions from HSR.

Overall, as shown in Table 2-2, the electricity intensity (in MJ/pkm) of numerous HSR vehicles range from 0.1 MJ/pkm to 1.28 MJ/pkm, depending on train size, speed profile, and average load factor. Specifically, Japan's Shinkansen HSR (Kato et al. 2005; Taniguchi, 1992) is the most energy efficient model which only consumes 0.1-0.13 MJ of electricity per pkm. In contrast, the proposed California high-speed rail, with 1200 seats and only 25% utilisation rate as one of the assessed scenarios, has the highest electricity intensity at 1.28 MJ/pkm (Chester and Horvath, 2012).

As the key focus of this review, I can now compare the HSR energy intensity from this literature survey against the energy intensity of aircraft over stage length. Based on Figure 2-4, the average energy intensity over all types of aircraft on short-haul routes (below 500 km) is 5.71 MJ/pkm, whereas the average value of the electricity intensities of HSR in Table 2-2 is 0.35 MJ/pkm. Therefore, on average aircraft is about 16 times more energy intensive than HSR on short-range stage length, which corresponds best to HSR travel distances. In comparison, on long-distance

routes (above 1000 km) the average energy intensity of aircraft is 2.54 MJ/pkm, 7 times higher than that of HSR trains.

Finally, through the literature survey as shown in Table 2-2, it is found that although China has an HSR network that account for about 65% of the world's total HSR track length (UIC, 2018), there are few studies on the Chinese HSR energy end-use and CO₂ emissions. Studying the emissions reduction potential from the HSR substitution for aviation in China is particularly interesting, because HSR has already become a strong competitor to domestic air transport. As a result, the emission savings from substituting aviation by HSR could potentially contribute to climate change mitigation from China's passenger air transport sector. In order to assess the competition effects of HSR to air transport, in the next section, I will review previous literature that focus on the competition between the two high-speed transport modes.

2.3.3 Previous research on HSR substitution for air transport

In the previous section a comparative review is presented on the energy intensities of air transport and HSR. It is found that as aircraft energy intensity strongly depends on stage length (Figure 2-4), air transport is about 16 times more energy intensive than HSR on routes below 500 km and about 7 times more energy intensity on routes longer than 1000 km. Therefore, by substituting HSR for aviation, CO₂ emissions could be greatly saved from passenger air transport. Previous literatures have largely focused on two aspects of the HSR-Air transport competition, which will be reviewed separately in this section.

Empirical studies of the post-HSR impacts on air transport

One strand of research uses econometric models to assess how airline markets (represented by either airline total supply or total demand) are affected by the

introduction of HSR lines. In these models, the HSR effects are typically captured by a dummy variable indicating whether there is HSR service in the parallel markets of air transport, with GDP, population, route distance, and existence of hub airports, etc. as other control variables (Jimenez and Betancor, 2012; Dobruszkes et al, 2014; Albalade et al, 2015; Wan et al, 2016; Chen, 2017; Zhang et al, 2017). To this end, one challenge from a data engineering perspective is to match the commencement of different HSR lines with airline-route data. Given the complicated nature of a HSR project which involves multi-stage planning, financing, and construction, segments on an HSR route are completed often at different times. One example is the HSR line connecting Beijing and Guangzhou in China, on which the Wuhan-Guangzhou segment was completed in December 2009, whereas the segments of Zhengzhou-Wuhan and Beijing-Zhengzhou were completed three-years later in September and December 2012, respectively. Thus, the HSR between Beijing and Guangzhou is available only after the completion of the entire HSR line in December 2012. As a result, to capture the HSR competition effects in both time and space accurately, the specific opening date of a HSR segment must be included as an indicator for which HSR begins to compete with air transport.

Furthermore, the literature in this strand consistently show that the competitiveness of HSR over air travel is highly dependent on route distance. Some find that HSR imposes a competition pressure mainly on routes less than 500 km (Jimenez and Betancor, 2012; Taniguchi, 1992), and others indicate that HSR market share with respect to air transport becomes modest for routes beyond 650 km (Albalade and Bel, 2012). Given the diminishing competition effects of HSR over distance, Chen (2017) assessed the impacts of two Chinese HSR lines on air transport demand for three distance groups, i.e. short-haul (less than 500 km), medium-haul (500-800 km),

and long-haul (more than 800 km). He found that HSR caused a 34%-35.7% decline in air travel demand on medium-haul routes, while the competition becomes less fierce when the travel distance is either below 500km or above 800km. Using the same distance grouping, Wan et al. (2016) demonstrated that on routes with direct HSR entries, airline annual seat capacity has an average 67% decrease on short-haul routes (less than 500 km) while the decline in medium haul (500-800 km) is only about 4%. In comparison, some studies evaluate the competitiveness of HSR not by distance but by travel time, arguing that given the heterogeneous speeds of HSR, route distance is an imperfect proxy of travel time which is the definitive determinant of competitive advantage (Albalade et al., 2015). For instance, Klein (1997) concluded that the TGV-Atlantique in France led to a sharp reduction in air travel in journeys between 90 and 180 minutes, and Fu et al. (2012) argued that optimal routes for HSR should have 3-4 hours journey time.

In the majority of cases, the HSR substitution has been examined from an airline supply perspective, i.e. impacts of HSR entries on flight frequency or airline seats capacity (Bilotkach et al, 2010; Jimenez and Betancor, 2012; Albalade, et al, 2015; Wan et al, 2016). A few studies also evaluated the HSR impacts on airline passenger demand and airfares (European Commission, 2006; Chen, 2017), but the scope of these analyses is limited. Albalade et al (2015) empirically studied the impact of HSR on air transport over the period of 2002-2010 in countries with the largest HSR networks in Europe, namely Spain, France, Germany, and Italy (together, the four countries alone accounted for 93% of the total European HSR network in 2010). Their study shows that following the introduction of HSR, there is a significant reduction in airline total seat capacity while flight frequency does not undergo such significant drop. This implies that in Europe, airlines appear to adopt a strategy of maintaining their

competitiveness in terms of flight frequency while replacing their fleet by smaller aircraft to reduce operating costs in the competition with HSR services. Applying a difference-in-difference (D-in-D) estimation approach, Wan et al. (2016) further demonstrated the HSR impacts on airline supply in the Northeast Asian market covering China, Japan, and South Korea. They found that HSR entries lead to a more significant drop in airline seat capacity in China than that in Japan and South Korea especially on short-haul and long-haul routes. However, Wan et al.'s (2016) findings are constrained by the scope of their data. Only routes from eight airports of the three countries are included; and given that their data covers the time period of 1994-2012, during which the Chinese HSR was still at the early stage of development (in 2012 China had only 25 HSR segments completed, and this number increased to 76 by the end of 2015), the HSR effects is likely to be under-estimated.

As mentioned earlier, there are also a limited number of studies assessing HSR impacts on air transport demand and airfares. The lack of research on this aspect is mainly due to data availability. Using a similar method to Albalade et al. (2015) but assessing the HSR impacts on both airline supply and demand in China, Chen (2017) concluded that after the introduction of China's two major HSR corridors (Beijing-Shanghai HSR and Beijing-Shenzhen HSR), there has been a 28.2% reduction in aviation passengers and 26.4% reduction in flights from inter-city travel on these two HSR lines specifically. Zhang et al. (2017) assessed the HSR impact on China's big three airlines on 22 HSR-affected routes and found that air passenger demand drops by 39% and 31% on routes with distance between 0-500km and 500-1000km, respectively, and the average airfares decreases by 6-9% after the introduction of HSR. In addition, the price difference between airfare and HSR fare also has significant negative effects: with 10% increases in the price difference, air transport demand will

drop by 18-22%. In a report for the European Commissions, Steer Davies Gleave (2006) found sharp reductions in airfares in Europe attributable to competing HSR services to the level even below corresponding rail fares. However, only eight intra-European HSR-Air routes are included in this study, and therefore again their findings are hardly applicable at system scale.

For all the empirical studies reviewed above, the climate impacts of HSR entries to air transport are left unaddressed. This is mainly constrained by the methodology adopted where the HSR effects are captured simply by a dummy variable, which makes it impossible to assess the net emissions savings from the HSR substitution for air transport. To fill this gap, a novel method is required that can empirically compare airline's operational changes before and after HSR entries and evaluate the emissions savings resulting from that operating change.

Mode choice models between HSR and air transport

The second stream of research applies discrete choice models using survey data to estimate the transport modal split between air transport and HSR (Roman et al. 2007; Roman & Martin, 2010; Pagliara et al., 2012; Park & Ha, 2006; Clever & Hansen, 2008; Behrens & Pels, 2012). Comparing with the previous approach that captures the HSR competition effects by a dummy variable, the adoption of mode choice models estimates the probability of passengers choosing one transport mode over the other based on their utility functions, which contain a set of characteristics such as travel time, frequency, and travel costs. Passengers will always choose a transport mode that maximizes their utility. Hence, the discrete choice models provide additional insights on the HSR-Aviation competition from a traveller behaviour perspective. The key constraint of this approach is that it requires disaggregate data

through passenger surveys, and acquiring such data is relatively expensive, especially when researchers aim to study multiple HSR lines. As a result, existing literature using discrete choice models rarely evaluate the HSR substitution effects at a network scale.

Mode choice models are more widely used in studies assessing HSR-Aviation modal split for individual corridors in Europe. Most studies in this area have focused on Spain, the country with the largest HSR network in Europe (UIC, 2018). Roman et al. (2007), Roman and Martin (2010), and Pagliara et al. (2012) applied different forms of logit models to analyse the market share split on the corridor connecting Madrid and Barcelona. Using a mixed revealed- and stated preference data, Roman et al. (2007) predicted that HSR in Spain will only obtain no more than 35% of market share when competing with air transport. As an extended study, Roman and Martin (2010) updated this result and predicted that the market share of HSR ranges from 43% to 48%, with a total demand of HSR on this corridor between 2.7 million and 3.2 million per year. Similar findings were concluded by Pagliara et al (2012) that on the route of Madrid - Barcelona, market share taken by HSR was lower than expected at only 44.15%, and that in order to obtain 50% of the market, HSR on this corridor would need a 3.76% fare reduction.

Studies on other HSR corridors across the world include Seoul-Daegu in South Korea (Park and Ha, 2006) and Tokyo-Osaka and Osaka-Fukuoka in Japan (Clever and Hansen, 2008). Interestingly, results from this group of work suggest that the above HSR lines have a much larger negative impact on air transport compared to the Madrid-Barcelona corridor in Spain. For instance, Park and Ha (2006) projected that after the HSR operating on the Seoul-Daegu corridor, only 14% of passengers would prefer to travel by air. Clever and Hansen (2008) found that HSR in Japan almost takes all market share due to its great reliability on schedule and high service frequency. As

a result, air transport in the domestic Japanese market has to focus only on frequent point-to-point flights in a few selected markets.

Given that most existing studies focused on individual corridors, the avoided emissions from substituting HSR for air transport is rarely assessed at this scale. However, if the HSR competition effects could be studied at network scale, the question of how HSR substitution for air transport will contribute to emissions savings at system wide becomes a more much interesting topic.

When comparing energy use and emissions between two transport modes and estimating their net emissions savings via modal substitution, it is important to consider not only the operational emissions but also the non-operational phases such as vehicle manufacturing and infrastructure construction, etc. Therefore, in order to correctly understand the climate impacts of the modal substitution, one must assess its emissions through end-of-life processes. A few studies that describe a lifecycle approach to estimating emissions inventories of different transportation modes exist. These are reviewed in Section 2.4.

2.4 Studies on Lifecycle Emissions from HSR and Air Transport

Section 2.3 suggests that shifting traffic from aviation to the more energy efficient HSR could have a significant potential to reduce emissions in the aviation sector. However, the question of how much emissions will be saved from the substitution of HSR for aviation requires rigorous assessments on the lifecycle emissions from both modes. Studies assessing the lifecycle emissions of different

transport modes are reviewed next, followed by a review on approaches to estimating lifecycle emissions savings from modal substitution.

2.4.1 Lifecycle emissions assessment for transportation

Before Chester (2008), studies assessing the environmental impacts of passenger transportation have largely focused on the operational phase of transporting people from origins to destinations, which left non-operational components, such as vehicle manufacturing, infrastructure construction, and fuel production unaddressed (except a handful studies on the lifecycle environmental effects of automobiles including MacLean (1998), Sullivan et al. (1998), Delucchi (1997), and Weiss et al. (2000)). To fill this knowledge gap, Chester (2008) in his PhD thesis provided a comprehensive, systematic study of the lifecycle environmental effects of passenger modes in the United States, covering automobiles, buses, railways, and air transport.

Chester (2008) estimated the lifecycle CO₂ emissions of these transport modes for vehicle, infrastructure, and fuel components, respectively, and provided detailed energy inputs and emissions outputs for various stages of each lifecycle component. Based on his work, a few subsequent studies are conducted (Chester & Horvath, 2010; Chester & Horvath, 2012). Most relevant to the interests of this dissertation, Chester (2008) specifically evaluated the lifecycle emissions of the proposed California High-speed Rail (CAHSR) project based on information published by the CAHSR Authority (2005) and provided valuable parameters that allows researchers to evaluate the lifecycle CO₂ emissions of other HSR systems. In addition, he also assessed lifecycle emissions of passenger air transport, including emissions for manufacturing small- (represented by Embraer 145), medium- (represented by Boeing 737), and large

(represented by Boeing 747) size aircraft, respectively, and the emissions for constructing airport, which has not been evaluated at all from a lifecycle framework.

2.4.2 Lifecycle emissions savings from HSR-Aviation substitution

Previous environmental assessments of HSR have largely discussed potential energy and emissions reductions of HSR over other modes based on direct electricity consumption and corresponding power plant emissions (Givoni 2007, Andersson & Lukaszewicz 2006, Janic 2003, van Wee et al., 2003, Lynch, 1990). However, the lifecycle emissions savings from substituting HSR for other energy-intensive modes is rarely touched. Studies that adopted the lifecycle assessment approach (Chester, 2008; Chester & Horvath, 2010; Yue et al., 2015) tend to evaluate the lifecycle emissions of HSR and other transport modes individually, without explicitly assessing the associated net lifecycle CO₂ emissions savings from substituting HSR for air transport.

Attempts do exist, however, by Chester and Horvath (2012), who simulated the consequential lifecycle environmental effects of introducing the CAHSR system, based on the demand projections by the CAHSR Authority (PB, 2011). PB (2011) estimated that, by 2040, the CAHSR between San Francisco and Los Angeles would displace 5.8 billion auto VKT and 5.1 million air trips annually. As a result of the projected demand replacement, emissions per VKT compared to a “without HSR” case would be reduced by 12% under the 2020 renewable energy mix (Chester & Horvath, 2012).

In summary, although the lifecycle emissions assessment has not been applied to existing HSR networks, Chester (2008) and Chester and Horvath (2012) provided a framework to evaluate the potential emissions savings of HSR substitution for air

transport based on the proposed California HSR corridor. Adopting a similar approach, researchers could evaluate the net lifecycle emissions savings from substituting HSR for air transport in other countries, such as China, which has developed large networks for both HSR and aviation systems. A case study of China's HSR substitution for air transport, especially from a lifecycle perspective, would provide valuable insights on how the high-speed modal substitution as a system-wide mitigation policy option could contribute to emissions reduction in passenger air transport sector.

2.5 Conclusions

The studies reviewed in this chapter focus on two emissions mitigation strategies for the passenger aviation sector.

The first strategy relates to the market-based environmental policies for air transport, where three significant research gaps from the previous literature are identified. First of all, given that MBMs will effectively increase airlines' operating costs, airlines are expected to respond to the increase through adjusting their pricing mechanism. However, it is found that airline operating costs are not explicitly captured in any of the existing airline pricing models but are instead represented by proxy variables such as O-D distance (Borenstein, 1989; Brueckner et al., 1992; Morrison et al. 2001; Hofer et al. 2007; Zhang et al., 2012). These models are therefore not capable of reflecting the effects of changes in operating costs on airfares, nor can they inform policy makers how fares would change as response to changes in different types of operating costs resulting from the MBMs, such as a tax on fuel costs versus a tax on airline's landing costs. Secondly, a review on previous literature of cost pass-through shows that the empirical cost pass-through analysis has largely focused on industries

with large amount of high-frequency time series data, such as consumer fuel markets and electricity markets, however, there is very limited research on the cost pass-through for the passenger air transport sector due to a lack of time series data on cost and airfares at global scale. Without empirical evidence on airline cost pass-through, the review of the existing literature of potential impacts of the market-based environmental policies on aviation suggests that most of these studies had to rely on either the pre-assumed cost pass-through rates (Meleo, 2014; Meleo, et al., 2016) or model-based estimates (Girardet & Spinler, 2013; Pagoni & Pasarakis-Kalouptsi, 2016). Therefore, research findings in this area are highly uncertain and may result in misleading policy recommendations. Finally, it is found that previous studies have largely focused on the domestic U.S. airline market where the most complete data on airfares are publicly available. Thus, they could only provide limited insights to markets in other parts of the world due to distinct market characteristics. In order to evaluate the potential impacts of a global MBMs such as CORSIA described in chapter 1, the cost pass-through effects must be assessed not just for the U.S. market but all other regional airline markets as well.

The second mitigation strategy is the modal substitution of high-speed rail (HSR) for air transport, which would improve the transport energy efficiency at system scale. For this strategy, my review finds that compared to the average electricity intensity of HSR, the average energy intensity of air transport is about 16 times higher on short-range routes (below 500 km) and 7 times higher on long-range routes (above 1,000 km). As a result, substituting air transport by HSR could greatly reduce CO₂ emissions. Existing studies on the competition between HSR and air transport mainly consists of two strands. The first strand using econometric models empirically assesses the impact of HSR entries to airline markets, with the HSR effects simply captured by

a dummy variable (Jimenez and Betancor, 2012; Dobruszkes et al, 2014; Albalade et al, 2015; Wan et al, 2016; Chen, 2017; Zhang et al, 2017). The second strand adopts discrete choice models to predict market shares between the two transport modes, based on their utility functions containing a set of characteristics such as travel time, frequency, and travel costs. Studies adopting discrete modes largely focus on individual corridors (Roman et al. 2007; Roman & Martin, 2010; Pagliara et al., 2012; Park & Ha, 2006; Clever & Hansen, 2008; Behrens & Pels, 2012). Therefore, emissions savings from the HSR substitution for air transport at network scale remains largely unknown.

This review suggests that, although studies exist on evaluating lifecycle emissions of HSR and air transport (Chester, 2008; Chester & Horvath, 2010; Chester & Horvath, 2012), estimating the net lifecycle savings of CO₂ emissions from HSR substitution for air transport is still in its infancy. In particular, since China has developed very large networks for both HSR and aviation systems, a case study of China's HSR substitution for air transport, especially from a lifecycle perspective, would provide valuable insights on the extent to which the high-speed modal substitution as a system-wide mitigation policy option could contribute to emissions reduction in passenger air transport sector. This would allow policy makers in both China and other countries to evaluate whether it is beneficial to pursue further infrastructure investments in HSR to achieve a low-carbon transportation system.

Based on the identified research gaps summarised in this chapter, the research questions and corresponding research objectives for this dissertation are described in the following chapter, Chapter 3.

Chapter 3 Research Questions and Objectives

The literature review in Chapter 2 concludes that, as emissions mitigation strategies, both the market-based environmental policies and high-speed rail substitution for air transport especially in China have not been extensively studied. This chapter presents the main research questions of this dissertation, along with a description of the key research objectives that aim to address each of the proposed research questions.

3.1 Research Questions

As a result of the literature review in Chapter 2, the research questions that this dissertation aims to address are as follows:

RQ1: What is the potential impact of market-based measures designed to reduce aviation emissions on airline pricing behaviour?

- How could airline operating costs affect airline average fares through cost pass-through and how might the cost pass-through elasticities vary by operating cost type and regional market?
- What could be the airline pricing response to market-based environmental policies for aviation, such as a carbon tax?
- To what extent could the effects of a market-based environmental policy differ by world region?

RQ2: What has been the impact of high-speed rail on domestic aviation CO₂ emissions in China?

- How much operational CO₂ emissions savings has China's HSR system achieved through substituting domestic air transport since its introduction?
- How have Chinese airlines responded to the direct entries of HSR through adjusting annual total seat capacity?
- How large could be the additional environmental benefit from substituting HSR for air transport in a low-carbon electricity generation system in China?

RQ3: How large could be the lifecycle net emissions savings from substituting HSR for air transport in China in the future?

- What could be the future demand for domestic air transport under the existing 2015 HSR network and the future planned 2025 HSR network?
- How much additional airport capacity might be needed to meet the future aviation demand in China under the 2015 and the 2025 HSR network?
- What are the lifecycle CO₂ emissions for future air and HSR transport in China?
How much marginal net savings of lifecycle CO₂ emissions could the substitution of the enhanced 2025 HSR system for air transport achieve, compared to the 2015 HSR network?

3.2 Research Objectives

In order to answer the above research questions, this dissertation has the following key research objectives:

With respect to RQ1, the research objectives are:

- To develop an econometric itinerary-based airfares model that can explicitly capture airline operating costs and important supply and demand factors;
- Using the model, to empirically estimate cost pass-through elasticities by operating cost type and by regional markets;
- To test a market-based emissions reduction policy based on the estimated cost pass-through elasticities and assess if airlines' pricing responses to the MBMs differ by regional markets.

With respect to RQ2, the research objectives are:

- To empirically compare airline supply changes in terms of seat capacity between 2000 and 2015 *before* and *after* the entry of HSR;
- To estimate the historical shifted traffic from aviation to HSR and the associated operational emissions savings;
- To test the emissions savings under lower carbon intensity of power generation.

With respect to RQ3, the research objectives are:

- To specify, estimate and test a demand model that projects aviation and HSR demands, taking into account the HSR competition to air transport;
- Using the model, to project future aviation demands under the 2015 and the future planned 2025 HSR network, under various future scenarios;
- To develop a method that matches airport capacity to the projected aviation demand and estimate how much additional capacity would be required;
- To calculate the lifecycle CO₂ emissions for both HSR and air transport based on the projected demands and compute the marginal net savings of lifecycle emissions from the enhanced HSR substitution for air transport.

Chapter 4 Modelling Airline Cost Pass-Through within Regional Aviation Markets³

As concluded in Chapter 2, studies assessing the impact of market-based environmental policies in aviation rely on various scenarios of airline cost pass-through, because there is little empirical evidence with respect to the impacts of airline operating cost on airfares. Indeed, until today, the operating cost effect has been indirectly measured by proxy variables such as distance, fuel price, and aircraft sizes. This chapter develops an airfare model that explicitly captures airline operating costs. Using a feasible generalized two-stage least squares (FG2SLS) approach, I estimated coefficients of airline fuel cost per passenger, non-fuel cost per passenger, and non-fuel cost per flight for all world regions. A comparison of the estimated cost pass-through elasticities conducted across regional markets suggests that airlines may respond to the cost increases differently, depending on the cost type and the market airlines operate within. Based on the estimated coefficients, I systematically evaluate the potential impacts of introducing a carbon tax within two major regional markets with distinct cost pass-through elasticities.

³ See a published version of this chapter at: <https://doi.org/10.1177/0361198118792337>

4.1 Introduction

To achieve carbon-neutral growth in international aviation, the International Civil Aviation Organization (ICAO) has introduced a Market-based Measures (MBMs) scheme. The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), which is planned to be introduced in 2021, will effectively increase airline fuel cost (ICAO, 2016). Airlines will respond to the higher fuel cost by adjusting technology, operations, and airfares. However, higher fares in a competitive market may result in – depending on the elasticity of demand relative to supply – lower sales and market shares. Therefore, airlines have to strike a balance between recovering cost increases and maintaining their market share. Cost pass-through rates will manifest this balance. Additionally, as airline operating costs consist of several components, an airline could potentially be more vulnerable to changes in one cost component than another. For example, an increase in fuel cost may have greater impacts to some airlines than a comparable absolute increase in landing cost. Thus, it would be interesting to assess the potential pricing responses of airlines to changes in different operating costs under competition.

As concluded in Chapter 2, there is little empirical evidence with respect to airline cost pass-through. As a result, most of the studies that aim to assess the extent to which MBMs could lead to aviation emissions reduction had to assume rates of cost pass-through. Therefore, more empirical research is needed on this subject in order to understand the potential pricing response of airlines to MBMs on the aviation sector. Estimating the cost pass-through requires estimating airfares in a competitive environment. The literature review in Chapter 2 finds that how airlines set fares has been studied extensively, albeit with a focus on the U.S. domestic airline market.

Existing literature has found several factors that affect airfares, such as market structure and competition, passenger demand, load factor, and flight delays. In contrast, few studies modelled the operating cost effects on airfares explicitly. Instead, in most cases, distance, fuel price, and aircraft sizes have been used as proxy variables of airline costs. However, these proxy variables cannot capture changes in specific airline costs, and thus are not useful to quantify how much of airline's cost burden is passed through to passengers via airfares, which is the focus of this research.

Findings from this chapter contribute to the existing literature in the following ways. First, it provides empirical evidence on airline cost pass-through to future research that otherwise would have to rely on presumed cost pass-through rates when evaluating the economic impacts of MBMs on the aviation sector. Secondly, having estimated the fare model at a global scale, results from this work have implications to both developed and developing airline markets. This is particularly important to regions beyond the U.S. domestic market, where aviation emissions are projected to grow more rapidly over the next 20-30 years (Yan et al., 2014) yet have not been explored in the current body of airline pricing studies. Finally, coefficients estimated from this model could be used to evaluate potential impacts of MBMs such as CORSIA on airline pricing behaviour, but also to help policy makers to design other aviation emissions reduction policies. Notably, this airfare model is a core component of the global aviation systems model AIM2015 (Dray et al., 2018).

The next section describes the data underlying this work, the three operating cost variables of the main interest, and the econometric model specification. The model estimation and the empirical findings are then discussed in Section 4.3. Based on the estimated pass-through elasticities, a carbon tax policy scenario that effectively increases airline fuel cost is evaluated in Section 4.4 for two regional markets with

distinct cost pass-through elasticities. Using the AIM2015 Model, the scenario analysis compares the possible system-wide impacts of increased airline cost on airfare, demand, and CO₂ emissions. Section 4.5 offers conclusions for this chapter.

4.2 Data and Empirical Model

This section presents the airfare model developed in this chapter. Datasets used to construct the model variables are firstly described, followed by a detailed discussion of the critical operating-cost variables. The section concludes with the specification of the airfare model.

4.2.1 Data

As discussed in Chapter 2, a major hurdle of assessing the pricing responses of airlines to changes in operating costs is the lack of comprehensive and high-frequency time series data on prices and airline costs at a global scale. As a first attempt in existing literature to empirically estimate airline cost pass-through for all regional markets around the world, this study uses cross-sectional data of average airfares of all airline markets globally for the year 2015 from the Sabre Market Intelligence database (SABRE, 2016). Notably, although the fare model estimated on the cross-sectional data provides short-run cost pass-through elasticities, which might be lower than the pass-through elasticities estimated on time-series data, empirical findings from this work still have a valuable contribution to the existing literature given that there is very limited evidence of cost pass-through for the airline sector.

In addition to airfares, data describing passenger demand, market shares, flight frequency, and route characteristics are also either directly obtained or constructed from the Sabre database. Enroute and airport landing charges by aircraft size class are

provided by the RDC airport charges database (RDC, 2017). Fleet data is obtained from Flight-Global (2017) and used to derive aircraft type by flight segment.

With the data described above, flight itineraries connecting different Origin-Destination (O-D) region-pairs are grouped into intra-regional markets (e.g. Europe-Europe) and inter-regional markets (e.g. North America-Europe). Airfares (including taxes) of a given flight are weighted by the number of passengers paying different observed prices based on booking classes, and this weighted average flight airfares of all flights operating on a same itinerary are then aggregated as the annual average price on this itinerary, weighted by number of passengers on each flight.

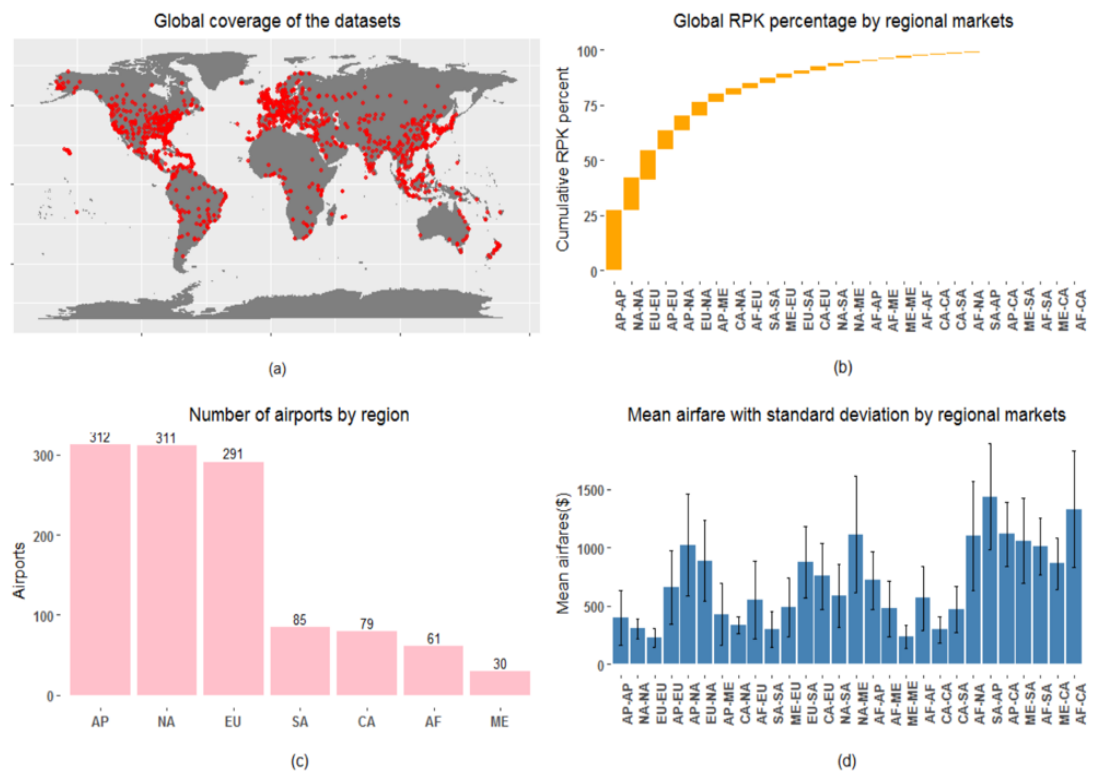
Table 4-1. Aircraft size classes used in this dissertation.

Size Category	Approx. seat range	Reference aircraft	Reference engine
1. Small regional jet	30-69	CRJ 700	GE CF34 8C5B1
2. Large regional jet	70-109	Embraer 190	GE CF34 10E6
3. Small narrowbody	110-129	Airbus A319	V.2522
4. Medium narrowbody	130-159	Airbus A320	CFM56-5B4
5. Large narrowbody	160-199	Boeing 737-800	CFM56-7B27
6. Small twin aisle	200-249	Boeing 787-800	GENx-1B67
7. Medium twin aisle	250-299	Airbus A330-300	Trent 772B
8. Large twin aisle	300-399	Boeing 777-300ER	PW4090
9. Very large aircraft	400+	Airbus A380-800	EA GP7270

The unit of observation is a unique route between an O-D airport-pair, connected by a maximum of three flight segments (see Appendix B: percentage of direct-, one-stop, and two-stops routes in total O-D pairs in each regional market). To ensure a robust model estimation, routes with very low demand are removed. I restrict low-traffic routes to those with a share of the total O-D passengers on a given city-

pair below 5%, and annual passengers fewer than 52 (1 passenger per week) in intra-regional markets or 520 (10 passengers per week) in inter-regional markets.

Lastly, this work uses nine aircraft size classes adapted from the Sustainable Aviation (2015) aircraft categories. Aircraft are assigned to classes based on number of seats and MTOW. Each size class category has a reference aircraft. Table 4-1 shows the aircraft size classes used in this study.



NOTE: NA=North America, CA=Central America, SA=South America, EU=Europe, ME=Middle East, AF=Africa, AP=Asia and Pacific

Figure 4-1. Descriptive summary of datasets used in this chapter.

Figure 4-1 describes four key aspects of the cleaned data. The entire data sample covers all continents over the world (a). The largest five markets in terms of RPK are AP-AP, NA-NA, EU-EU, AP-EU, and AP-NA, and the top 22 region-pair markets account for 95% of the global total RPK (b). The share of RPK is closely linked to the total number of airports available in each region (c). As 78% of the global airports are located in AP, NA, and EU, markets connecting these regions account for

the largest proportion of the global RPK. Finally, from (d) we can see that overall fares are higher in inter-regional markets than in intra-markets (also with greater variation in fares), and the highest average fares are found in those smallest markets potentially because of the limited supply.

4.2.2 Airline Operating Costs Variables

Given that the focus of this chapter is the airline cost effect on airfares, before introducing the model specification, the key operating cost variables included in the model are firstly described. As discussed in Chapter 2, airline operating cost have been largely measured by proxy variables such as distance, fuel price, and dummy variables for aircraft sizes in previous airfare models (Hofer et al., 2008; Dresner & Tretheway, 1992; Zou & Hansen, 2014). Such proxy variables cannot directly quantify the effects of changes in airline cost to airfares. In contrast, this fare model includes operating cost variables that have this capacity.

As shown in Figure 4-2, airline operating cost are calculated by aircraft size class (Table 4-1) firstly on flight segment basis. Costs are calculated for seven categories, namely fuel, crew, aircraft financing, aircraft maintenance, aircraft landing charges, passenger landing fees, and overhead cost. Fuel cost on a given segment is calculated as the product of total fuel burn and jet fuel price. Fuel burn from aircraft operation (take-off, climb, cruise, descent, landing, and taxi) by aircraft size class and by segment is estimated using the PIANO-X aircraft performance model (Lissys Ltd, 2017). Given that jet fuel prices do not vary significantly by world region (EIA, 2019), Jet-A fuel price in the U.S. in 2015 is used to derive fuel cost for all flight segments globally. Fuel cost of a given segment differs from other segments mainly because the

total fuel burn, which is determined by segment distance, average load factor, and the type and age of aircraft used, could vary significantly across flight segments.

Besides fuel cost, cost for crew, aircraft financing and maintenance are estimated by the AIM2015 Direct Operating Cost (DOC) Model (Al Zayat et al., 2017); aircraft landing charges and passenger landing fees at airports by aircraft size and by flight segment are obtained from the RDC airport charges database (RDC, 2017). After calculating operating cost by aircraft size class on a segment basis, the total cost of each cost category on a given flight segment is then aggregated over the aircraft type.

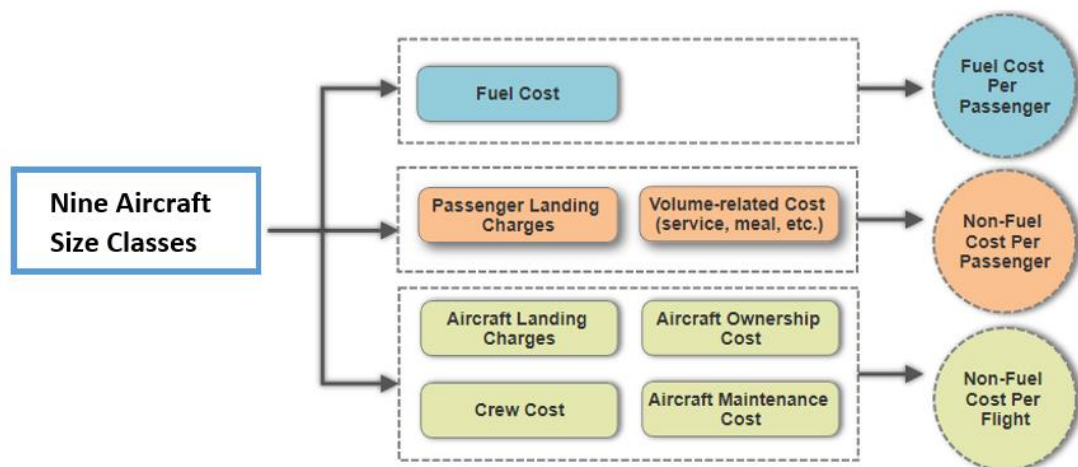


Figure 4-2. Procedure for constructing airline operating costs variables.

The total cost by the seven cost categories on a given segment is then averaged differently as three groups, i.e. fuel cost per passenger, non-fuel cost per passenger, and non-fuel cost per flight. Fuel cost and non-fuel cost are distinguished because fuel cost is generally the single largest cost component that has shown great fluctuations over the past 15 years (EIA, 2019), whereas other cost components have been relatively stable over time. Additionally, as segment total fuel cost and non-fuel passenger cost are determined by the number of passengers onboard, they are averaged by passenger numbers as per-passenger cost. In contrast, non-fuel flight cost are

averaged by flight frequency because each aircraft's flight-based costs (Figure 4-2) are fixed and do not vary with the number of enplaned passengers.

Having calculated the average fuel cost per passenger, non-fuel cost per passenger, and non-fuel cost per flight on a segment basis, these values are matched to segment(s) flown by a given flight itinerary and summed over all segments covered as the itinerary-specific average costs, for all itineraries.

Eq.(4-1) to Eq.(4-3) mathematically show the procedures described above:

$$(FuelCostPerPax)_{mkn} = \sum_{l \in Legs} \frac{\sum_{f,l} FuelC_{f,l} Freq_{f,l}}{Pax_l} \quad \forall Legs \in mkn \quad (4-1)$$

$$(NonFuelCostPerPax)_{mkn} = \sum_{l \in Legs} \frac{\sum_{f,l} (PaxLndC + VolC)_{f,l} Pax_{f,l}}{Pax_l} \quad \forall Legs \in mkn \quad (4-2)$$

$$(NonFuelCostPerFlt)_{mkn} = \sum_{l \in Legs} \frac{\sum_{f,l} (FltLndC + CrewC + MtnC + OwnC)_{f,l} Freq_{f,l}}{Freq_l} \quad \forall Legs \in mkn \quad (4-3)$$

where $FuelC_{f,l}$ in Eq.(4-1) represents fuel cost of an aircraft in size class f flying on segment l ; $Freq_{f,l}$ denotes annual flights under this aircraft size class on segment l ; and Pax_l is annual enplaned passengers flying this segment. Thus, the fuel cost per passenger on itinerary mkn is the sum of fuel cost per passenger of all segments ($Legs$) on mkn . Similarly, in Eq.(4-2), $(PaxLndC + VolC)_{f,l}$ is passenger landing fees and volume-related cost on aircraft size f flying segment l ; and $Pax_{f,l}$ is the annual enplaned passengers of aircraft size f on segment l . Lastly (Eq.4-3), segment cost of aircraft landing charges ($FltLandC$), crew cost ($CrewC$), maintenance cost ($MtnC$), and ownership cost ($OwnC$) on segment l is averaged by annual segment flights ($Freq_l$). The non-fuel cost per flight on itinerary mkn is the sum of flight cost per flight of all segments covered by itinerary mkn .

4.2.3 Model Specification

After a comprehensive review in Chapter 2 (see Table 2-1) on the key determinants of airline pricing, besides the operating cost variables discussed previously, I also control for all other key factors in the model specification, as such passenger demand, flight frequency, market competition, delay, and route structure. Moreover, a novelty in this work lies on the inclusion of a term with LCC dummy variable interacted with the fixed effects for the combination of origin and destination country pairs. Although the presence of low-cost carriers (LCCs) has been proved to have significant negative impact on airfares in the U.S. domestic airline market, this effect has rarely been tested for international routes (e.g. direct, short-haul routes in the western European market) or domestic markets in other world regions, such as China and India. Therefore, by including this interaction term, the airfare model developed in this study is more inclusive not only because it has the capability of comparing the LCC effect on airfares for all regional markets that have low-cost carriers but also because it well controls for the possible effect of LCCs on airline cost pass-through.

Specification of the econometric model are shown in Eq.(4-4):

$$\begin{aligned}
 \ln(\text{Fare})_{mkn} = & \beta_0 + \beta_1 \ln(\text{FuelCostPerPax})_{mkn} + \beta_2 \ln(\text{NonFuelCostPerPax})_{mkn} \\
 & + \beta_3 \ln(\text{NonFuelCostPerFlt})_{mkn} + \beta_4 \ln(\text{Freq})_{mkn} + \beta_5 \ln(\text{Pax})_{mkn} \\
 & + \beta_6 \ln(\text{LoadFactor})_{mkn} + \beta_7 \ln(\text{RouteShare})_{mkn} \\
 & + \beta_8 \ln(\text{CUIMean})_{mkn} + \beta_9 \ln(\text{RouteHHI})_{mkn} + \beta_{10} \ln(\text{AirportHHI})_{mkn} \\
 & + \beta_{11} (\text{Nlegs})_{mkn} + \beta_{12} (\text{HubsPass})_{mkn} \\
 & + \sum_{od=2,3,4\dots} \delta_{od} (\text{LCC}_{mkn} * \text{FE_OD}_{od}) + \varepsilon_{mkn}
 \end{aligned}
 \tag{4-4}$$

where m , n , and k denote origin-, destination-, and connecting airport(s), respectively; o and d denote origin country and destination country, and ε is the random error.

Table 4-2. Definition of the fare model variables.

Variable	Description
Fare	Average airfare (including taxes) on a given route, weighted by passengers of each flight operated on this route.
FuelCostPerPax	The sum of average fuel cost per passenger of all flight segments covered by a given route.
NonFuelCostPerFlt	The sum of average non-fuel per flight cost of all flight segments covered by a given route.
NonFuelCostPerPax	The sum of average non-fuel per passenger cost of all segments covered by a given route.
Freq	Annual flight frequency of a given route.
Pax	Annual passengers of a given route.
LoadFactor	Average load factor of a given route.
RouteShare	Share of passengers on a given route over its associated total O-D city pair passengers.
RouteHHI	Route-level Herfindahl-Hirschman Index (HHI), measured by the geometric mean of HHIs of flight segments covered by a given route.
AirportHHI	Endpoint airport-level market concentration, measured by the average HHIs at origin and destination airport.
CUIMean	Average airport Capacity Utilisation Index (CUI) of the endpoint airports, calculated as the ratio of average aircraft movements during 16-hours daytime at a given airport over the airport's declared capacity. The higher the CUI, the busier the endpoint airports.
Nlegs	The number of flight segments covered by a given route.
HubsPass	The number of hub airports covered by a given route.
LCC	Dummy variable equals 1 if LCC operates in a given route, 0 otherwise.
FE_OD	Fixed effects on O-D country pair, equals 1 if between country pair od ($od = 2, 3, 4, \dots$).

Table 4-2 provides a description of all variables included in Eq.(4-4). As discussed in Chapter 2, cost pass-through can be measured by either the absolute pass-through rate or the pass-through elasticity. This airfare model by being specified in a log-log form measures cost pass-through as elasticity, based on coefficients β_1 , β_2 and β_3 . Thus, these coefficients can be interpreted as the percentage change in airfares associated with a given percentage increase in each of the three operating costs, after controlling for other factors.

Airfares are determined by the complex interactions between supply and demand. The supply-side effect is mainly captured by airline operating cost. The three itinerary-specific average cost variables, namely fuel cost per passenger ($FuelCostPerPax_{mkn}$), non-fuel cost per passenger ($NonFuelCostPerPax_{mkn}$), and non-fuel cost per flight ($FuelCostPerFlt_{mkn}$), represent the average expenses on a given itinerary associated with carrying each onboard passenger or operating an aircraft. Coefficients β_1 , β_2 and β_3 are expected to have positive signs as one would expect airline operating cost to be positively correlated with airfares. The interest lies

on how the estimated elasticities could vary by cost type and by regional market. Besides airline operating cost, flight frequency is also a factor representing the supply-side effect on fares. Controlling for per flight cost and load factor, higher flight frequency would lead to higher total itinerary cost thus presumably higher airfares; thus, coefficient of frequency is expected to be positive.

The demand-side effect is captured in the model by itinerary passengers and average load factor. As shown in Table 2-1, itinerary passenger demand has a demonstrated negative effect on fares. Average load factor may affect airfares in either positive or negative way. According to Borenstein (1989), flights with high load factors fly full more often and are more likely to operate at peak demand times, during which the opportunity cost of aircraft in use on a route is higher, hence possibly increasing fares (positive); on the other hand, as the load factor increases, the quality of service decreases thus lowering consumers' reservation prices for flights (negative).

Market competition not only acts as a key factor in fare determination but has significant influence on airline cost pass-through as well (Koopmans & Lieshout, 2016). This airfare model captures the market competition effect through three types of variables, namely route share, airport- and route-level HHIs, and LCC dummy. As discussed in Chapter 2, the average Herfindahl-Hirschman Index (HHI)⁴ on a given itinerary and its endpoint airports are included to capture market competition at route and airport levels, respectively. Higher HHIs represent higher market concentration and thus lower competition; therefore, coefficients of these variables are expected to be positive. Increases in route share may lead to greater market power and prices, thus also expected positive signs. In addition to the HHI-based concentration variables and

⁴ The HHI is calculated as the sum of squared market shares of all airlines in respective markets.

route share, another dimension of market competition comes from the presence of LCCs. As discussed at the beginning of this section, the LCC dummy variable is interacted with the fixed effects on O-D country pairs, which indicates that, the extent to which LCCs could negatively affect airfares is dependent on which O-D country pair they operate in and the characteristics of the endpoint countries. Therefore, the varying effects of LCC competition on airfares could be compared across different O-D country pairs.

The flight delay effect on airfare is exogenously represented by the average capacity utilisation of endpoint airports. A higher capacity utilisation indicates that airports are operating closer to its full capacity, thus potentially having more flight delays. Delays may affect fares in either direction. If airlines face significant loss in demand due to flight delays on certain routes, they might reduce airfares to attract passengers; if flight delays cost airline more than the cost of the demand loss, airlines might pass this cost onto passengers through higher fare, thus having positive signs.

Route characteristics are also included as the number of segments and hub airports covered by a given itinerary. Controlling for airline operating cost (thus O-D distance) and load factor, increased connections may decrease the service quality and passengers' willingness to pay, thus negatively affecting airfares. Additionally, the effect of hub airports on fares could be either positive or negative; if more hub airports are used by a route, cost per passenger is lower due to the economy of density effect, leading to lower fares; on the other hand, the more hubs a route uses, the higher the cost of airport services (e.g. slots, ground facilities, etc.), hence possibly leading to higher fares. Finally, the unobserved effects of endpoint countries on airline pricing (e.g. trade flows between the O-D countries, taxes on airfares, etc.) are captured by the fixed effects for the combination of origin and destination countries.

4.3 Model Estimation Results and Discussion

In this section, the model estimation is briefly described, followed by interpretation and discussion of the estimated cost pass-through elasticities for all region-pair markets, based on estimated coefficients β_1 , β_2 and β_3 . Further analysis is then discussed regarding the cost pass-through if fares are broken down into parts that are fuel-related, aircraft-related, and non-fuel-passenger-related, based on the corresponding proportion of per-passenger cost on a given itinerary. I conclude this chapter with an analysis of the system-wide impacts of introducing a carbon tax in two regional markets with distinct cost pass-through elasticities on demand, fares, and CO₂ emissions, using the global air transport systems model AIM2015.

4.3.1 Model Estimation

As described in Chapter 2, airfare models are complicated by the endogeneity bias arising from the demand effects from fares, i.e. a change in demand by a change in airfares. In Eq.(4-4), this potentially affects six right-hand side variables, namely Pax, LoadFactor, RouteShare, Freq, RouteHHI, and AirportHHI. The number of O-D passengers on a given route is clearly endogenous as changes in fares also affect passenger demand. Average load factor of a given itinerary is determined by passenger demand and seat capacity thus is potentially endogenous as well. RouteShare, defined as the share of total O-D passengers on this city-pair using a given route, may be endogenous because it is a function of O-D demand (Pax). Similarly, HHIs are also potentially endogenous, given that airline's market share, which is input to calculate HHIs, is expected to be a function of the price it charges (Borenstein, 1989; Chi & Koo, 2009). Flight frequency may be endogenous because increases in frequency will

have lower per-flight cost, thus lowering fares, which in turn attract more demand, resulting in a change in frequency. After conducting the traditional Breusch-Pagan test (Breusch & Pagan, 1979) and the Hausman test (Hausman, 1978), I found that the null hypotheses of homoscedasticity and exogeneity can be rejected at the 0.1% level, indicating that heteroskedasticity exists and the six variables are endogenous.

To correct for the endogeneity and heteroskedasticity bias, I estimate the model using a feasible generalized two-stage least squares (FG2SLS) procedure, with lagged Pax, LoadFactor, RouteShare, RouteHHI, AirportHHI and Freq in year 2014 as instrumental variables (IVs). The estimation procedures are: (1) estimate OLS residuals from the reduced-form equation; (2) regress the log of the squared residuals over all the exogenous variables (including the IVs); (3) estimate the error variance from the fitted values in step (2); (4) apply 2SLS with the dependent variable, the explanatory variables, with all the IVs divided by the estimated error variance (Wooldridge, 2010; McFadden, 2017).

4.3.2 Results and Discussion

The airfare model specified in Eq.(4-4) is estimated and compared for intra- and inter-regional-pair markets separately. The full estimation results of coefficients for all intra- and inter-regional pair markets can be found in Appendix C and D, respectively. Notably, coefficients of the interaction between the LCC dummy and the O-D regional fixed effects are not included in Appendix due to space constraints; nevertheless, these coefficients are readily available under request.

To briefly discuss the model performance first, as can be seen in Appendix C and D, overall, using the FG2SLS estimation method the adjusted R^2 values range from 0.61 to 0.92 across the intra-regional markets and from 0.54 to 0.91 across the

inter-regional markets, indicating that the model can explain a significant proportion of the variance in airfares of these regional markets. Additionally, most coefficients have high statistical significance at least at the 5% level and have the expected signs based on the discussion in Section 4.2.3. Out of the total 66 coefficients of the main interest, i.e. the cost-related variables (β_1 , β_2 and β_3 in Eq.4-4), only 5 are not significantly different from zero, while the remaining 61 coefficients are all positive and statistically significant at least at the 5% level. This demonstrates that airlines do pass increases in fuel cost, non-fuel passenger cost, and non-fuel flight cost onto passengers through higher airfares. More importantly, the coefficients tend to vary in magnitude, depending on the specific type of costs that airlines pass through and the regional market in which they operate, and this will be discussed in more details next.

Table 4-3. Estimated Cost Pass-Through Elasticities (PTEs) on intra-regional markets, based on the FG2SLS estimations (Appendix C).

Market	Fuel Cost PTE	Flight Cost PTE	Passenger Cost PTE	Adjusted R^2
AP-AP	0.34-0.38***	0.21-0.25***	0.09-0.15***	0.898
NA-NA	0.25-0.27***	0.14-0.15***	0.15-0.18***	0.630
SA-SA	0.22-0.26***	0.32-0.41***	0.19-0.28***	0.917
EU-EU	0.19-0.22***	0.05-0.09***	0.04-0.08***	0.608
CA-CA	0.17-0.24***	0.11-0.18***	0.12-0.23***	0.897
AF-AF	0.10-0.18***	0.23-0.27***	0.05-0.19*	0.904
ME-ME	Not Significant	0.40-0.72***	0.33-0.62**	0.869

Note: *** Significant at the 0.1% level; ** Significant at the 1% level; * Significant at the 5% level

Table 4-3 reports the estimated pass-through elasticities (PTEs) of the three itinerary-specific average costs for the intra-regional markets, based on the estimated coefficients β_1 , β_2 and β_3 . Notably, PTEs are presented as a range given that the pass-through elasticities are computed within 95% confidence intervals.

Among the 7 intra-regional markets, 6 coefficients prove to be statistically significant for the fuel-cost variable at least at the 5% level. Airlines in AP-AP are found to be the most responsive to changes in fuel cost, with an estimated PTE between 0.34 and 0.38. The relatively high elasticity in AP-AP can be explained by the fact that fuel cost accounts for a larger share of total airline costs, due to a wider geographical coverage (i.e., ranging from Russia to Australia), compared to other intra-markets. This follows by NA-NA (0.25-0.27), SA-SA (0.22-0.26), and EU-EU (0.19-0.22), which have very similar pass-through elasticities within 95% confidence intervals. For every 10% increase in fuel cost, fares in CA-CA will increase by 1.7-2.4%. The elasticity with statistical significance is the lowest in AF-AF (0.10-0.18), which shows slightly lower than half of the fuel-cost PTEs in AP-AP (0.34-0.38). The only statistically insignificant fuel-cost PTE is found in ME-ME, suggesting that increases in fuel cost may not have an airfare impact in ME-ME. This could be attributed to the fact that the majority of routes in ME-ME are operated by Gulf national flag carriers which might be subsidised by cheaper fuel cost due to the region's proximity to oil production and refining facilities, leading to lower supply chain costs (O'Connell, 2011).

All seven estimates for the non-fuel flight cost are statistically significant at the 0.1% level. Sharply contrasting with the estimate for fuel-cost PTE, ME-ME is found to be the most responsive to changes in non-fuel flight cost. For each 10% increases in this cost, the mean of fares in ME-ME will increase by 4.0-7.2%. Once again, this result demonstrates that with the possible lower fuel cost, airlines in the ME-involved markets could be much more responsive to changes in the other major component of airline operating costs, i.e. the flight-based cost. In contrast, EU -EU is the least elastic to non-fuel flight cost changes, with an estimated PTE only between

0.05 and 0.09. SA-SA ranks the second most elastic market with a PTE at 0.32-0.41. Elasticities of the third to the sixth markets are AF-AF (0.23-0.27), AP-AP (0.21-0.25), NA-NA (0.14-0.15), and CA-CA (0.11-0.18), respectively.

All the seven non-fuel-passenger-cost PTEs are statistically significant at least at the 5% level. Similar to findings from the non-fuel-flight-cost PTEs, ME-ME (0.33-0.62) and SA-SA (0.19-0.28) are found also to be the most sensitive markets to the increases in this cost type. This follows by CA-CA and NA-NA markets, having estimated PTEs at 0.12-0.23 and 0.15-0.18 within 95% confidence intervals, respectively. Once again, EU-EU has the lowest PTE in this cost category, with every 10% increase in non-fuel per-passenger cost leading to only 0.4-0.8% fare increase.

Table 4-4. Estimated Cost Pass-Through Elasticities (PTEs) for inter-regional markets, based on the FG2SLS estimation results (see Appendix D).

Market	Fuel Cost PTE	Flight Cost PTE	Passenger Cost PTE	Adjusted R^2
CA-SA	0.27-0.34***	0.12-0.35***	0.05-0.19**	0.772
CA-NA	0.25-0.32***	0.07-0.11***	0.04-0.13***	0.671
EU-SA	0.23-0.34***	0.16-0.33***	0.02-0.11*	0.607
AP-EU	0.20-0.27***	0.19-0.25***	0.14-0.19***	0.772
AP-NA	0.18-0.25**	0.29-0.41***	0.23-0.31***	0.595
EU-NA	0.16-0.23***	0.20-0.30***	0.09-0.16***	0.539
CA-EU	0.15-0.31***	0.18-0.32***	Not Significant	0.651
AF-NA	0.12-0.30**	0.14-0.35***	0.11-0.30**	0.635
AF-AP	0.11-0.33*	0.34-0.45***	0.02-0.21*	0.825
NA-SA	0.09-0.18**	0.27-0.45***	0.03-0.13***	0.609
AF-EU	0.06-0.16***	0.19-0.28***	0.02-0.12*	0.855
AP-ME	0.03-0.15**	0.23-0.32***	0.09-0.20***	0.911
EU-ME	0.03-0.15**	0.42-0.51***	0.04-0.13***	0.870
AF-ME	0.02-0.24*	0.13-0.34***	Not Significant	0.861
ME-NA	Not Significant	0.30-0.54***	Not Significant	0.622

Note: *** Significant at the 0.1% level; ** Significant at the 1% level; * Significant at the 5% level.

Table 4-4 presents a summary of the estimated PTEs for all inter-regional markets, based on the FG2SLS estimation for coefficients β_1 , β_2 and β_3 . Given that the inter-regional markets connect two different regional markets with distinct characteristics, the estimated PTEs could provide additional insights. Out of 45 PTE estimates, only 4 are found not statistically significant and the remaining 41 PTEs are all statistically significant at least at the 5% level and have the expected positive signs.

Out of 15 estimated fuel-cost PTEs from the inter-regional markets, 14 have statistically significant coefficients at least at the 5% level. The only statistically insignificant PTE is found in ME-NA, while all other ME-associated markets, namely AP-ME (0.03-0.15), EU-ME (0.03-0.15), and AF-ME (0.02-0.24), have the lowest PTEs in this cost category, despite with statistical significance. This is similar to our findings in the intra-markets estimates, and again demonstrates that the ME-involved markets might be least affected by fuel cost increases. On the other hand, two markets involving Central America have the highest fuel-cost PTEs. They are CA-SA (0.27-0.34) and CA-NA (0.25-0.32). AP-EU and AP-NA follow closely with an estimated PTE at 0.20-0.27 and 0.18-0.25, respectively, within 95% confidence intervals. EU-NA and CA-EU have similar estimated PTEs at 0.16-0.23 and 0.15-0.31, respectively. Following them, two AF-related markets, AF-NA and AF-AP, also have almost identical pass-through elasticities, ranging from 0.11 to 0.33. Finally, just slightly higher than the PTEs of the ME-involved markets, fuel-cost PTEs of NA-SA (0.09-0.18) and AF-EU (0.06-0.16) are also very similar.

Turning to the estimated flight-cost PTEs for inter-regional markets, similar to the results found in the intra-regional markets, the non-fuel flight-cost PTEs of all inter-regional markets are statistically highly significant at the 0.1% level. This finding may imply that policy interventions in increasing non-fuel flight cost could have the

most universal effects on airline pricing globally. Nevertheless, the effects still differ significantly in magnitude among these markets. Consistent with the findings of the intra-markets, the ME-involved markets are the most responsive to the non-fuel flight cost changes. Markets with the highest flight-cost PTEs are mostly associated with Middle East, namely EU-ME (0.42-0.51), ME-NA (0.30-0.54), and AP-ME (0.23-0.32). AF-ME has lower elasticity yet is still comparatively high in magnitude at 0.13-0.34. Additionally, AF-AP (0.34-0.45), NA-SA (0.27-0.45), and AP-NA (0.29-0.41) also have very high pass-through elasticities for increase in flight cost. Moreover, PTEs of EU-SA, AP-EU, EU-NA, CA-EU, and AF-NA all range from 0.15 to 0.35 within 95% confident intervals. CA-NA has the lowest elasticity to this cost type, i.e. with 10% increases in the per flight costs, fares are found to only increase by 0.7-1.1%.

Lastly, 3 out of 4 PTEs that are found statistically insignificant across all inter-regional market estimations come from the non-fuel-passenger-cost category. In addition, the values of PTEs of this category are overall smaller than those of the other two operating cost categories. For instance, AP-NA has the highest elasticity in this category but only at 0.23-0.31, which is lower than both the PTE of the most fuel cost-sensitive inter-market AP-EU (0.27-0.34) and the PTE of the most flight-cost sensitive market EU-ME (0.42-0.51). The second highest passenger-cost PTE is found in AF-NA at 0.11-0.30. The remaining statistically significant estimates of non-fuel passenger-cost PTEs are all below 0.20, with the lowest elasticities found in AF-EU (0.02-0.12) and EU-SA (0.02-0.11). Thus, overall, increases in non-fuel per passenger costs may have the smallest impact to airline pricing.

Overall, my empirical findings provide statistical evidence that airlines do pass through increased operating costs onto passengers to various extent across different regional markets. However, all the estimated cost pass-through elasticities are found

to be below 0.5, after controlling for other supply, demand, and competition effects on airfares. This can be explained by two possible reasons. First, the airline sector is a highly competitive market where most of airlines operate at margins, therefore, if too much cost increase is passed through to fares, airlines may experience reduction in market share and overall profits. Secondly, as the model is estimated on cross-sectional data, it gives short-run cost pass-through elasticities which are in general smaller than the long-run elasticities, as discussed in Section 2.2.4. On the other hand, it is found that increases in airline non-fuel flight cost could impact airline pricing across all regional markets, albeit at various extent. In contrast, increases in airline fuel cost are less likely to affect most of the ME-involved markets, given the statistically insignificant pass-through elasticities estimated from these markets. Finally, changes in non-fuel passenger cost are found to have the least impact to fares, with all other factors being constant.

4.3.3 Further Analysis on Cost Pass-through

Having estimated the cost pass-through elasticities using the airfare model, in this section I further explore the cost pass-through of airlines in a relatively “unconventional” way. Given that each cost component accounts for a varying proportion of airline’s total operating costs across different itineraries, increases in individual cost component may have stronger impact in percentage terms to the cost-related part of fares than its impact to the whole fare price. In order to explore this issue, this time I recalculate all average cost variables as per-passenger cost⁵, i.e. fuel cost per passenger, non-fuel flight-cost per passenger, and non-fuel passenger-cost per

⁵ Fuel cost and non-fuel passenger cost remain unchanged as per-passenger cost, whilst segment flight cost is not divided by total flights but by total segment passengers, and the segment-specific average flight-cost per passenger is then matched to each itinerary by the segment(s) used and summed over all segments on this itinerary, as average itinerary flight cost per passenger, similar to Eq. (4-1) and (4-2).

passenger; this way their proportions are comparable on a given itinerary. Following that, I then calculate the part of fares that are fuel-related, non-fuel flight-related, and non-fuel passenger-related, based on the corresponding proportion that is linked to the specific cost category.

As a simple example, based on my calculation, in 2015 on the non-stop route between New York (JFK Airport) and Los Angeles (LAX Airport), the average fuel cost per passenger is about \$74, the average non-fuel flight cost per passenger is about \$85, and the average non-fuel passenger-related cost is about \$47. The observed average airfare on this route is \$389.5. Therefore, in this analysis airfare on this route is broken down into the fuel-related part at \$140 (\$389.5 multiplied by the fuel-cost proportion of the total cost at about 36%), the aircraft-related part at \$161 (the non-fuel flight-cost accounts for about 41% of the total cost), and the non-fuel passenger-related part at \$89 (the non-fuel passenger-cost proportion is about 23%).

Then, the relationship between not the whole fare price but the fuel-related part of fare (Y_{mkn}) and the fuel cost ($FuelCostPerPax_{mkn}$) on itinerary mkn is expressed as:

$$\begin{aligned} \ln(Y)_{mkn} = & \alpha + \beta_1 \ln(FuelCostPerPax)_{mkn} + \beta_2 \ln(Freq)_{mkn} + \beta_3 \ln(Pax)_{mkn} + \\ & \beta_4 \ln(LoadFactor)_{mkn} + \beta_5 \ln(RouteShare)_{mkn} + \\ & \beta_6 \ln(CUIMean)_{mkn} + \beta_7 \ln(RouteHHI)_{mkn} + \beta_8 \ln(AirportHHI)_{mkn} + \\ & \beta_9 (Nlegs)_{mkn} + \beta_{10} (HubsPass)_{mkn} + \sum_{od=2,3,4\dots} \delta_{od} (LCC_{mkn} * \\ & FE_{OD_{od}}) + \vartheta_{mkn} \end{aligned} \quad (4-5)$$

where the fuel cost pass-through elasticity is estimated as coefficient β_1 . Note that for consistency all other variables in the airfare model are still included in Eq.(4-5). Similarly, the cost pass-through elasticity of non-fuel flight cost per passenger is estimated on the flight-related part of fares, and the cost pass-through elasticity of non-fuel passenger cost is estimated on the non-fuel-passenger-related part of fares.

Table 4-5. Estimated cost pass-through on the specific cost-related parts of fares.

Market	Fuel Cost PTE	Adjusted R^2	Flight Cost PTE	Adjusted R^2	Passenger Cost PTE	Adjusted R^2
AP-AP	0.98-1.01***	0.93	0.81-0.84***	0.89	0.58-0.63***	0.77
NA-NA	0.95-0.96***	0.81	0.76-0.77***	0.71	0.54-0.58***	0.48
SA-SA	0.88-0.93***	0.94	1.04-1.11***	0.93	0.75-0.95***	0.87
EU-EU	0.83-0.86***	0.73	0.38-0.41***	0.68	0.35-0.39***	0.67
CA-CA	0.67-0.76***	0.92	0.53-0.62***	0.91	0.39-0.52***	0.88
AF-AF	0.46-0.58***	0.93	0.45-0.58***	0.92	0.36-0.56***	0.83
ME-ME	0.22-0.33***	0.79	0.86-0.92***	0.88	0.74-0.93***	0.90
CA-SA	0.86-1.07***	0.87	0.81-1.05***	0.83	0.53-0.85***	0.75
CA-NA	0.88-0.92***	0.76	0.75-0.79***	0.70	0.40-0.50***	0.60
EU-SA	0.77-0.89***	0.64	0.41-0.58***	0.55	0.78-0.88***	0.68
AP-EU	0.72-0.78***	0.85	0.49-0.56***	0.77	0.93-0.98***	0.70
NA-SA	0.67-0.83***	0.66	0.31-0.48***	0.57	0.49-0.70***	0.43
EU-NA	0.64-0.70***	0.50	0.38-0.45***	0.43	0.78-0.85***	0.50
AP-NA	0.53-0.61***	0.55	0.58-0.65***	0.49	0.96-1.04***	0.65
CA-EU	0.58-0.75***	0.67	0.33-0.50***	0.61	0.66-0.82***	0.65
AF-NA	0.50-0.71***	0.69	0.41-0.66***	0.58	0.78-0.96***	0.59
AF-AP	0.47-0.62***	0.83	0.36-0.51***	0.77	0.56-0.76***	0.73
AF-EU	0.49-0.58***	0.91	0.28-0.37***	0.85	0.64-0.76***	0.77
AP-ME	0.39-0.49***	0.93	0.67-0.77***	0.91	0.65-0.79***	0.82
EU-ME	0.25-0.35***	0.91	0.62-0.75***	0.88	0.63-0.72***	0.78
ME-NA	0.22-0.37***	0.67	0.42-0.57***	0.63	0.32-0.58***	0.55
AF-ME	0.14-0.28***	0.90	0.55-0.64***	0.85	0.29-0.41***	0.77

Note: *** Significant at the 0.1% level; ** Significant at the 1% level; * Significant at the 5% level.

Table 4-5 reports the estimated pass-through elasticities of each average per-passenger cost to its related part of fares for all regional markets, using the FG2SLS method. As shown in Table 4-5, all the cost-pass through estimates are statistically highly significant at the 0.1% level and have the expected positive signs. The adjusted R^2 ranges from 0.50 to 0.94 for the fuel-cost PTE estimates, from 0.43 to 0.93 for the

flight-cost PTE estimates, and from 0.43 to 0.90 for the non-fuel passenger-cost PTE estimates.

The most important difference between the PTEs estimated on the whole price of fares (Table 4-3 and 4-4) and the PTEs estimated on only the specific cost-related part of fares is that, the pass-through elasticities estimated by the latter are significantly larger. This result confirms my hypothesis that, in percentage terms, an increase in fuel cost is found to have much stronger impact to the specific part of airfares that is fuel-related, compared to its influence on the whole price of airfares. This suggests that airlines may actually pass through a large proportion of the fuel cost increases on to the fuel-related part of fares, although the absolute amount of this cost pass-through may only lead to a small increase in percentage terms in the whole fare price, as shown in my main results (Table 4-3 and 4-4).

Nevertheless, some of the main findings from the previous section still stand in this estimation. For example, AP-AP remains the most fuel-cost sensitive market in the intra-regional markets, where the fuel-related part of fares could increase by 9.8-10.1% resulted from a 10% increase in the fuel cost per passenger. In comparison, ME-ME is still found to be affected the least by fuel cost changes, with a fuel-cost PTE only at 0.22-0.33. The rank of the intra-regional markets by the sensitivity to fuel-cost changes is largely unchanged compared to Table 4-3. On the other hand, assessing the impact of non-fuel flight cost to the flight-related part of fares leads to slightly different conclusions to the regional effects on cost pass-through. SA-SA becomes the most responsive market to an increase in the non-fuel flight cost per passenger with an estimated PTE at 1.04-1.11, while it is closely followed by ME-ME (0.86-0.92), which is found to be the most elastic market to the flight-cost increase in the main result (Table 4-3). The flight-related part of fares in EU-EU remains the least

price-responsive to an increase in flight-cost per passenger, with an estimated PTE at 0.38-0.41. Finally, among the intra-regional markets, the non-fuel passenger cost is still found to have a relatively small impact, compared to the impact of the other two per-passenger costs on their related-parts of fares. The regional difference is largely unchanged, with the top two markets for this cost type as SA-SA (0.75-0.95) and ME-ME (0.74-0.93) while the market with the lowest PTE is still EU-EU (0.35-0.39).

Similarly, for the inter-regional markets, estimating cost pass-through on the specific cost-related parts of fares gives larger pass-through elasticities than the results shown in Table 4-4, whilst the cross-region heterogeneity is largely the same. For a 10% increase in fuel cost per passenger, the fuel-related part of fares could increase the most in CA-SA by 8.6-10.7%, followed closely by CA-NA with an increase by 8.8-9.2%. In contrast, the ME-involved markets are still found to have the lowest fuel-cost PTEs. On the other hand, increases in non-fuel flight-cost per passenger could increase the flight-related part of fares the most in CA-SA (0.81-1.05), CA-NA (0.75-0.79), and the ME-related markets (e.g. AP-ME at 0.67-0.77, EU-ME at 0.62-0.75, and AF-ME at 0.55-0.64), whilst the lowest flight-cost PTE is found in AF-EU at 0.28-0.37. Finally, when only assessing the cost pass-through to the non-fuel-passenger-related part of fares, which in general accounts for the smallest share in price, an estimated PTEs of the non-fuel cost per passenger are considerably larger. The top two markets with the highest PTEs are AP-NA (0.96-1.04) and AP-EU (0.93-0.98) and the market with the lowest PTE is AF-ME at 0.29-0.41.

Overall, this section further assesses the cost pass-through of itinerary per-passenger cost to its related part of the fares. The results suggest that increases in airline cost have much stronger impacts on the specific part of fares that is directly linked to it. However, the regional effects on cost pass-through are largely unchanged.

4.4 AIM2015 MBM Policy Scenario Analysis

To conclude this chapter, I compare the potential impacts of an emissions reduction policy that increases airline fuel costs on airfares, demand, and CO₂ emissions in two major regional markets, using the updated global aviation systems model AIM2015. The airfare model developed in this work is a core component of the AIM2015. A brief description of AIM2015 is firstly presented, followed by the policy scenario simulation and discussion.

4.4.1 Aviation Integrated Model 2015

The Aviation Integrate Model (AIM) is a global aviation systems model which simulates interactions between passengers, airlines, airports and other system actors into the future, with the goal of providing insight into how policy levers and other projected system changes will affect aviation's externalities and economic impacts (Dray et al., 2018). The model was originally developed in 2006-2009 (Reynolds et al. 2007) and was used in a number of research projects (ATSlab.org).

AIM has been substantially updated to AIM2015, as part of the ACCLAIM project (2015-2018), which aims to produce a tool that can assess the local and system-wide impacts of adding capacity at constrained airports. Figure 4-3 shows the model structure of AIM 2015 (Dray, et al. 2018). Models which have been added or updated for AIM2015 are shown with a white background in Figure 4-3. As can be seen, a number of major updates on previous versions of AIM has been made, including a demand and fare module, a large part of the aircraft performance and cost module, an aircraft size choice model in the aircraft movement module, and a few integrated externalities modules, etc. (Dray, et al. 2018).

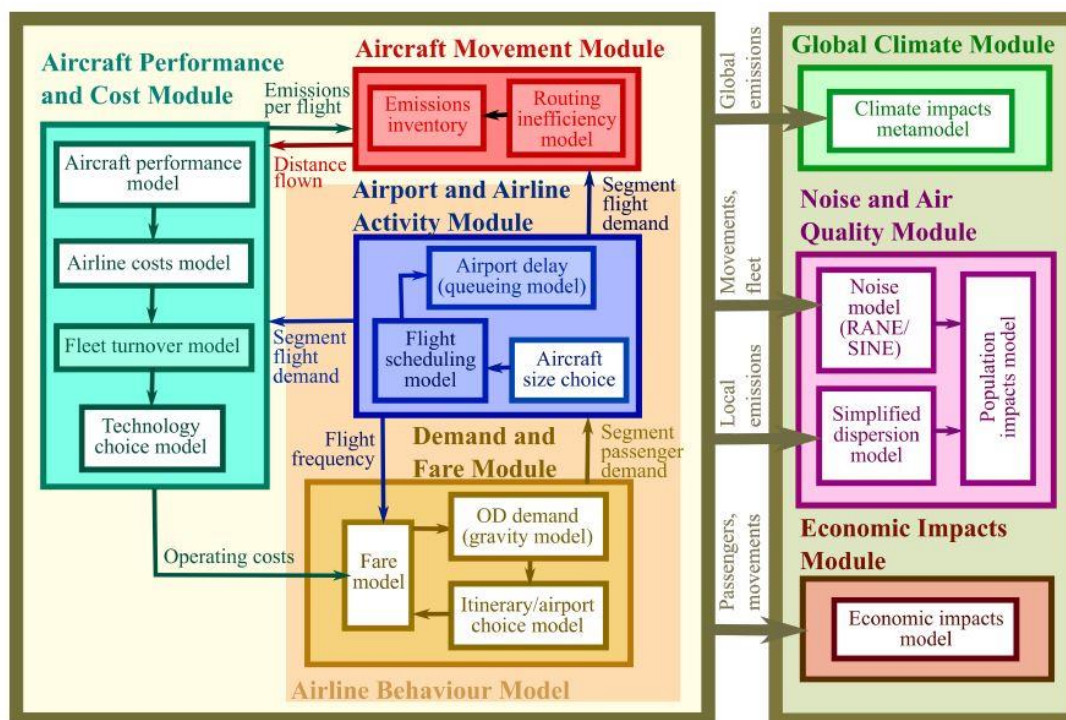


Figure 4-3. Model structure of the updated AIM2015.

As shown in Figure 4-3, the airfare model developed in this study sits in the demand and fare module of the AIM2015. This module consists of three major components, i.e. a gravity-type O-D demand model that projects true origin-ultimate destination passenger demand between a set of global cities; an itinerary choice model that distributes the O-D city pair demand between available itineraries; and this airfare model that predicts itinerary-specific average airfares which could in turn affect the itinerary and O-D city pair demand. The three models interact extensively with each other, with the fare model balancing the demand side with the supply components of AIM2015, expressed via airline operating costs.

Therefore, using the AIM2015 I can simulate possible system-wide impacts on aviation demand, airfare, and CO₂ emissions of policies that increase airline cost, such as putting a tax on jet fuel consumption. These impacts are simulated within the AIM2015 where increased fuel cost by the carbon tax firstly affect airfares via cost pass-through, and changes in itinerary airfares then impact itinerary demand and

ultimately the O-D city pair total demand. Finally, the direct CO₂ emissions associated with the influenced aviation demand could provide insights on the effectiveness of this carbon tax policy on emissions reduction for the global air transport sector.

4.4.2 Policy Scenario Analysis

Using the AIM2015, a carbon tax policy is simulated over three baseline scenarios. I use country-level population and GDP per capita scenarios from O'Neill et al. (2013), and oil price scenarios from the UK government (DECC, 2015). Specifically, the three baseline scenarios are:

- 1) The low-growth scenario: low GDP growth to 2050, high oil prices, and pessimistic technology adoption (late availability date, high cost, low benefit).
- 2) The central-growth scenario: medium GDP growth to 2050, central oil prices, and mid-range technology adoption.
- 3) The best-growth scenario: high GDP growth to 2050, low oil prices, and optimistic technology adoption (early availability date, low cost, high benefit).

Two regional markets with different fuel-cost pass-through elasticities (Table 4-3) are selected, i.e. AP-AP (0.34-0.38) and EU-EU (0.19-0.22). A carbon tax is hypothetically introduced from 2015 at \$36/tCO₂, which linearly increases to \$150/tCO₂ by 2050. Notably, this is a relatively high carbon tax scenario, compared to the highest carbon tax in the EU ETS to date at \$36 (European Climate Exchange, 2017). Figure 4-4 depicts firstly the key scenario inputs of GDP growth and oil prices, followed by the scenario projections for both regional markets. Notably, the final CO₂ impacts of the carbon tax depend on two stages: airlines' pricing response to the increased fuel cost after the carbon tax is introduced (i.e. through cost pass-through elasticity) and then the demand response to price changes (i.e. elasticity of demand).

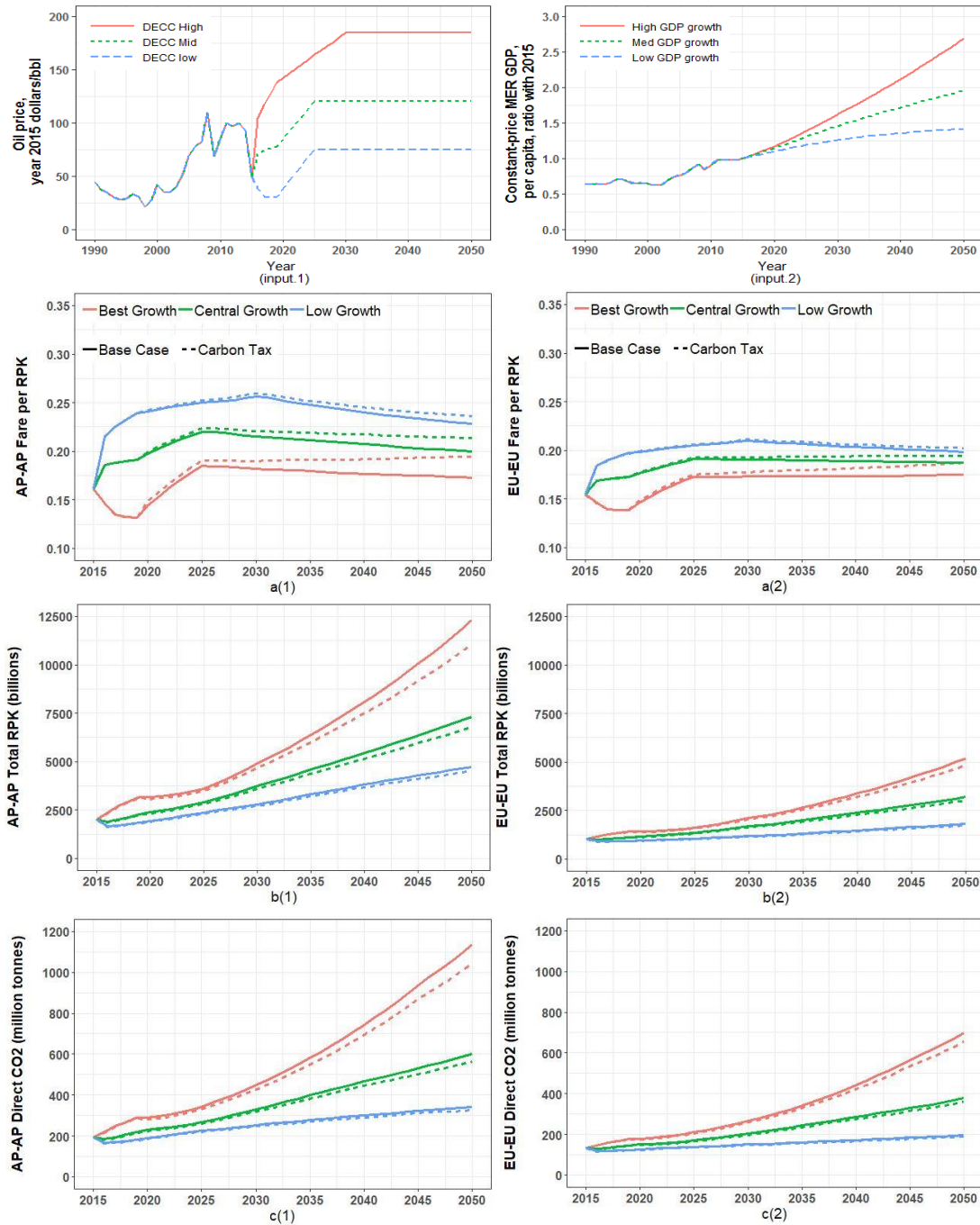


Figure 4-4. AIM2015 projections for demand, average fare, and direct CO₂ emissions in AP-AP and EU-EU regional airline markets.

Figure 4-4 depicts the projections of airfare per RPK, total RPK, and direct CO₂ emissions under the base case (“no policy intervention”) scenario as solid lines and the projections under the carbon tax scenario as dashed lines. The first result panel (a1 and a2) shows the projections for airfares. As can be seen, given that the best-growth scenario assumes low fuel prices (DECC low in Figure 4-4 input.1), fare per

RPK is predicted to be the lowest under the best-growth case for both regional markets. In contrast, the low-growth case has the highest fare per RPK. Notably, the projected airfares are found to follow closely with the fluctuations of future fuel prices, which manifests the effect of fuel cost on fares. Compared to the base case, it is shown that in both regional markets, airfares per RPK are higher under the carbon tax policy, as a result of airline cost pass-through. Importantly, given that AP-AP has higher estimated fuel cost pass-through elasticity at 0.36 (± 0.02) than EU-EU at 0.20 (± 0.02), fare per RPK increases more strongly in AP-AP under the same carbon price. By 2050, fare per RPK in AP-AP is projected to be 12.8% (the best-growth case), 7.4% (the central-growth case), and 3.6% (the low-growth case) higher than those of the base-case projections. In comparison, fare per RPK in EU-EU is projected to increase by only 6.4% (the best-growth case), 3.5% (the central-growth case), and 1.6% (the low-growth case), respectively. This result implies that under a global carbon tax policy, air passengers in different regional markets could face different extent of fare increases.

The second result panel (b1 and b2) then shows the projections for aviation demand in terms of annual RPK. Driven by the assumed high GDP growth and low fuel prices, RPK in AP-AP from 2015 to 2050 under the base-case best-growth scenario could see a 512% increase, compared to a 264% increase under the base-case central-growth scenario and a 135% increase under the base-case low-growth scenario. However, the strong increase in demand in AP-AP could be compromised by the increased airfares under the carbon tax policy. It is predicted that if the carbon tax is introduced, between 2015 and 2050, RPK in AP-AP may have smaller increase by 451% under the high-growth case, by 237% under the central-growth case, and by 124% under the low-growth case, respectively. On the other hand, demand in the more

matured EU-EU market follows a similar trend but has considerably smaller growth. Without policy interventions, RPK in EU-EU is project to increase by 391% under the best-growth case, 203% under the central-growth case, and 71% under the low-growth case, respectively. In comparison, the demand growth is also expected to be less compromised in EU-EU under the carbon tax policy, due to the relatively moderate increase in airfares. From 2015 to 2050, RPK in EU-EU with the carbon tax could increase slightly slower by 362% under the best-growth scenario, by 192% under the central-growth scenario, and by 67% under the low-growth scenario, respectively.

Finally, the third result panel (c1 and c2) depicts projections of direct CO₂ emissions associated with aircraft operation in AP-AP and EU-EU market. Unsurprisingly, CO₂ emissions are closely linked with aviation demand. Similar to the demand growth, AP-AP is found to have considerable increase in CO₂ emissions. Under the base case, emissions in AP-AP could increase by 496% in the best-growth future, by 241% in the central-growth future, and by 119% in the low-growth future, respectively. This strong growth is likely to be compromised under the carbon tax due to the less significant increase in demand. With the carbon tax, CO₂ emissions in AP-AP may have slightly smaller growth by 431% in the best-growth case, by 206% in the central-growth case, and by 106% in the low-growth case. In comparison, EU-EU is predicted to have less significant growth in CO₂ emissions than AP-AP. With no policy interventions, direct CO₂ emissions in EU-EU could increase by 416% under the best-growth case, by 193% under the central-growth case, and by 67% under the low-growth case. If the carbon tax is introduced, less growth in CO₂ emissions is expected. Specifically, EU-EU direct CO₂ emissions under the carbon tax are predicted to grow by 391% in the best-growth case, by 183% in the central-growth case, and by 61% in the low-growth case, respectively.

4.5 Conclusions

The research presented in this chapter shows that airlines operating in different regional aviation markets may have distinct pricing responses to the market-based measures (MBMs) that increase airline operating cost, by explicitly modelling the cost pass-through of fuel cost per passenger, non-fuel cost per passenger, and non-fuel cost per flight. It contributes to the field by enabling future research to have more certainty on the possible cost pass-through of airlines when evaluating the economic impacts of MBMs to aviation, especially in world regions beyond the U.S. domestic market. To my best knowledge, this is the first study that empirically estimates airline cost pass-through under competition at a global scale.

By estimating an econometric airfare model using the FG2SLS approach, I found significant cross-region and cross-cost-type heterogeneity in the estimated cost pass-through elasticities. For example, the intra-Asia Pacific regional market is found to be most responsive to changes in fuel cost, whilst the Middle East-involved markets are less likely to be affected by such changes due to their estimated fuel-cost pass-through elasticities are not significantly different from zero. In comparison, changes in non-fuel flight costs are found to have positive pricing impacts to all regional markets, although it would be more difficult to design MBMs that can affect the largely-fixed flight-based operating cost. Increases in non-fuel per passenger costs are found to have the smallest impact to airfares.

Furthermore, given that each cost component accounts for a varying proportion of airline's total operating costs on a given itinerary, increases in individual cost component may have stronger impact in percentage terms to the specific cost-related part of fares than its impact to the whole fare price. In order to explore this issue, I

conducted an additional analysis where itinerary airfares are broken down into parts that are fuel-related, aircraft-related, and non-fuel-passenger-related. Although this approach “unconventionally” changes the dependent variable into the cost-related part of the fares instead of the observed airfares, important additional insights are found from this exercise. Specifically, the estimated cost pass-through elasticities to the cost-related part of fares are significantly larger, suggesting that a large proportion of increases in a given per-passenger cost is actually passed on to its related part of fares, although this cost pass-through only leads to a small increase in percentage terms in the whole fare price, as can be seen from the cost pass-through elasticities estimated on the observed fare price. Moreover, conclusions regarding the cross-region heterogeneity drawn from my main findings still largely stand in this analysis.

This chapter concludes with a policy scenario analysis of the potential system-wide impacts of introducing a carbon tax in different regional markets. Using the aviation systems model AIM2015 which incorporates my airfare model, the simulation suggests that carbon tax may lead to increase in airfares, slightly slower growth in demand, and eventually slightly less strong growth in direct CO₂ emissions.

Despite the useful contributions of this work to the existing literature, this study also has its limitations. Due to data constraints, the cost pass-through elasticities are estimated on the cross-sectional data, which provides short-run elasticities that may underestimate the effect of increased cost on airfares in the long-term projections. Thus, the CO₂ emissions savings simulated in AIM2015 might be underestimated, if the long-run cost pass-through elasticities were available. Also, the possible asymmetric pass-through could not be estimated either as it requires time-series data to capture temporal positive and negative changes in both price and cost.

Chapter 5 Assessing the Impact of High-Speed Rail on Domestic Aviation CO₂ Emissions in China⁶

The literature review in Chapter 2 concludes that given the significantly lower energy intensity of high-speed rail (HSR) compared to air transport, substituting HSR for aviation is a potential strategy to reduce CO₂ emissions from passenger air transport. However, there is a lack of empirical evidence on the system-wide emissions savings from the HSR substitution for air transport. Filling this research gap, this chapter examines the impact of HSR on reducing aviation CO₂ emissions in China. It demonstrates that investments into China's HSR system has already contributed to emissions reduction from domestic aviation. It is estimated that, through mode substitution for air transport, HSR generated a cumulative operational net saving of 6.5-7.4 million tonnes of CO₂ from 2009 to 2015. This amount is equivalent to 12-14% of 2015 domestic aviation emissions. Compared to the estimated historical emissions savings, a sensitivity analysis is conducted to test the impact of cleaner electricity generation to emissions savings from substituting HSR for air transport in China. With the dominating role of coal in China's current energy mix, this chapter concludes that HSR could have an even greater potential to reduce system-wide CO₂ emissions, if China achieved its climate pledge in the Paris Agreement in terms of decarbonizing its electricity generation sector by 2030.

⁶ Updated based on a published version of this chapter at: <https://doi.org/10.1177/0361198119835813>

5.1 Introduction

In 2015, the transport sector accounted for 15.7% of China's final energy demand and 10.6% of its energy related CO₂ emissions (IEA, 2017b). Transportation was thus the country's third largest source of CO₂ emissions. China has announced to cut its CO₂ emissions per unit of GDP by 60%–65% from the 2005 level by 2030 (NRDC, 2017). In order to achieve this goal, emissions reduction measures have been introduced in different industries, including the transport sector. Since the early 2000s, China has started to develop the world's largest high-speed rail (HSR) network; by the end of 2015, its total HSR track length reached 19,838 km, which represents 51% of the global HSR network (Ministry of Railways, China, 2015). This expansion of infrastructure has led to a strong increase in HSR ridership, from 7.34 million passengers carried in 2008 to 961.4 million in 2015 (China Statistical Yearbook, 2017). In 2016, China announced a HSR development plan that aims to expand its HSR network from the current "four-vertical and four-horizontal lines" structure to an "eight vertical and eight horizontal lines" structure by 2025, with a total track length of 38,000 km, nearly twice the current level (China State Council, 2016).

Domestic air transport in China has also experienced rapid growth in recent years. The annual domestic RPK has increased from 159.25 billion in 2005 to 556.57 billion in 2015 (China Statistical Yearbook, 2016). In 2015, 53.8 million tonne (Mt) CO₂ emissions were generated from domestic aviation, accounting for 5.6% of the total CO₂ emissions from the transport sector (IEA, 2017b). Additionally, domestic air traffic in China is projected to almost quadruple from 2016 to 2036 and become the world's largest air transport market with about 1,900 billion RPK (Airbus, 2017). Such growth would translate into a significant increase in CO₂ emissions from air transport.

Given its substantial growth and high speed, HSR has become a competitive alternative for inter-city travel in China. Competition from HSR has directly resulted in cancellations of some short-haul airline routes, such as Zhengzhou–Xi’an, Changsha–Guangzhou, and Zhengzhou–Changsha (Jiang & Zhang, 2016). As a result, there has been growing research interest in HSR-aviation competition effects. This chapter examines the historical emissions savings from the substitution of flights with high-speed trains since the introduction of the HSR system in China.

The main contributions of this chapter to the existing literature are threefold: (i) conducting a comparative analysis of the network development in China for HSR and air transport between 2010 and 2015; (ii) estimating the system-wide HSR substitution effects on air transport supply, using airline seat capacity data over the period from 2000 to 2015; (iii) examining the historical CO₂ emissions savings resulting from substituting HSR for air transport in China, together with a sensitivity analysis on the impact of cleaner electricity generation mix to emissions savings from the mode substitution. Note that in this study the net emissions savings are estimated for vehicle operational phase only, and the embedded emissions in non-operational phases (vehicle manufacturing and maintenance, infrastructure construction, maintenance, and operation, and fuel production) are out of scope for this study.

The next section of this chapter describes the data underlying this work, upon which a comparison of development of HSR and aviation networks in China is described. Section 5.3 empirically analyses changes in airline supply due to the HSR competition on a year-by-year basis. Based on the observed reduction in airline supply after HSR entries, Section 5.4 estimates the historical savings of CO₂ emissions from substituting HSR for air transport between 2009 and 2015. Finally, this chapter concludes with a sensitivity analysis that estimates additional emissions savings if

China had a cleaner electricity mix, compared with the observed energy mix, over the same period. Results of the sensitivity analysis are compared against the historical emissions savings to illustrate the greater emissions reduction potential from HSR substitution if China keeps decarbonizing its power generation sector. Section 5.5 offers conclusions for this chapter.

5.2 Data

A dataset was constructed comprising domestic city pairs using both air transport and HSR-related data. It includes all the non-stop airline routes connecting a set of 78 major Chinese cities. Inter-city air travel between these cities accounted for more than 90% of total RPK of the domestic Chinese aviation market in 2015. The sample consists of a panel of 16 years' annual flight frequency and seat capacity data between 2000 and 2015 for a total of 776 routes. A route is defined as a true origin-ultimate destination (O-D) city pair connected by non-stop flights. Each observation consists of a route-year pair, which has an HSR dummy equal to 1 if the route is also effectively connected by HSR in that year. In total there are 12,416 observations throughout the sample period.

Air transport supply data was obtained from Sabre Market Intelligence database (2016), which contains information on flight frequency, seats available, and the types of aircraft used by flight segment in each year. For HSR, information was collected on all HSR corridors under operation in China by the end of 2015. The collected information includes specific opening dates of these corridors, HSR train types operated on each corridor, their passing-by cities, and the HSR track length between each city pair (Ministry of Railways, China, 2015).

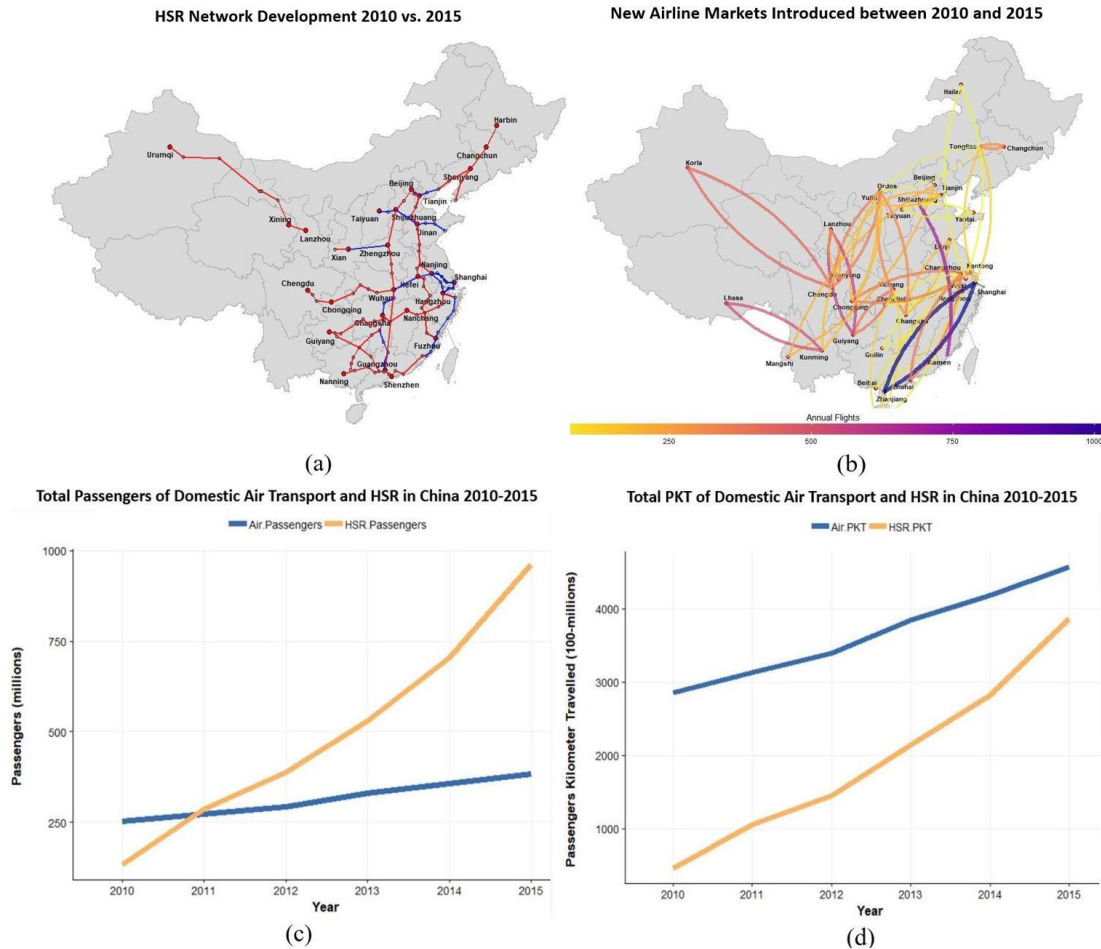


Figure 5-1. Comparison between HSR and domestic air transport networks in China: (a) HSR network development 2010 versus 2015, (b) new airline markets introduced between 2010 and 2015, (c) total passengers of domestic air transport and HSR, and (d) total PKT of domestic air transport and HSR, 2010-2015.

Firstly, Figure 5-1 provides an overview of the development of air transport and HSR networks over the sample period. From Figure 5-1(a), China's HSR network saw a considerable expansion between 2010 and 2015, increasing from a total track length of 5,100 km in 2010 (blue lines) to 19,838 km in 2015 (blue plus red lines). By the end of 2015, an HSR network that connects north and south and east and west of the country had been completed. During the same period, the domestic air transport network grew less strongly (Figure 5-1b). Only a few new city pair markets were introduced, of which Shanghai–Zhanjiang, Shijiazhuang–Xiamen, and Lanzhou–Guiyang had relatively heavy traffic with annual average of 500-1,000 flights.

Figure 5-1(c) and (d) depict the annual ridership and passenger-kilometre-travelled (PKT) of the two transport modes from 2010 to 2015, respectively. As can be seen in Figure 5-1(c), the number of passengers taking HSR increased strongly and surpassed passengers of domestic air transport in 2011, the year that China's busiest HSR corridor linking Beijing and Shanghai started operating. In terms of PKT, however, domestic air transport still dominates, albeit with slower growth than that of HSR, as shown in Figure 5-1(d).

5.3 Changes in Airline Supply After HSR Entries

This section provides the empirical evidence of diversion of airline supply due to HSR competition. Firstly, the data-preprocessing method used to allow a year-by-year comparison of airline seat capacity on routes with and without HSR competition is described. The two groups are matched to estimate the empirical changes of airline supply after the introduction of HSR.

5.3.1 HSR-Air Routes Treatment

To start the analysis, the entire sample was first divided into two groups: airline routes with HSR services in operation in parallel defined to be the affected group, and airline routes without HSR connection as the controlled (unaffected) group (Wan et al., 2016; Zhang et al., 2017). Given that the construction of segments on a given HSR corridor is often completed at different points in time, city pairs that are newly connected by HSR in each year are identified and moved from the "controlled group" to the "affected group". As such, the set of O-D pairs included in the two groups varies over time. Notably, as the analysis is based on annual data while entry of HSR may close to the end of a year and thus has very limited impacts on the air traffic in the

year of entry. To address this issue, for routes where HSR enters in the fourth quarter of the year, the “effective” entry year is considered as one year after the actual entry.

Earlier research (Wan et al., 2016) only accounted for HSR entry of “online” city pairs (city pairs that are directly linked by a single HSR corridor), in contrast, this work identifies both online and cross-line O-D pairs with HSR connections, making the sample size of the affected group significantly larger than those of the previous studies. Further, it is found that HSR is most competitive in short-distance (less than 500 km) markets (Jimenez & Betancor, 2012; Taniguchi, 1992; Wan et al., 2016), and its competitiveness declines as travel distance increases. Thus, the sample was also split by great circle distance range as short-distance (less than 500 km), medium-distance (500-1,000 km), and long-distance (more than 1,000 km).

After identifying city pairs in the affected group and the controlled group on a year-by-year basis, historical trends of the average seat capacity per O-D pair on the two groups are matched and compared over the period of 2000 to 2015. It is expected that, before HSR was introduced (the “pre-HSR era”), average seat capacity of the affected O-D pairs should follow similar trend of the city pairs in the controlled group. However, after HSR operating in these O-D pairs (the “post-HSR era”), average seat capacity of the affected routes may show evidence of a decline compared to the controlled routes, depending on the distance range. This possible decline in average seat capacity could be considered as the HSR substitution effect on airline supply, which is discussed in detail in the next section.

5.3.2 HSR Substitution Effect on Airline Supply

This section assesses the HSR substitution effects by distance range, through comparing the seat capacity trends of affected and controlled groups on a year-by-year basis, as described previously. Firstly, Figure 5-2 depicts the evolution of historical airline seat capacity of the two route groups on short-distance range (< 500 km).

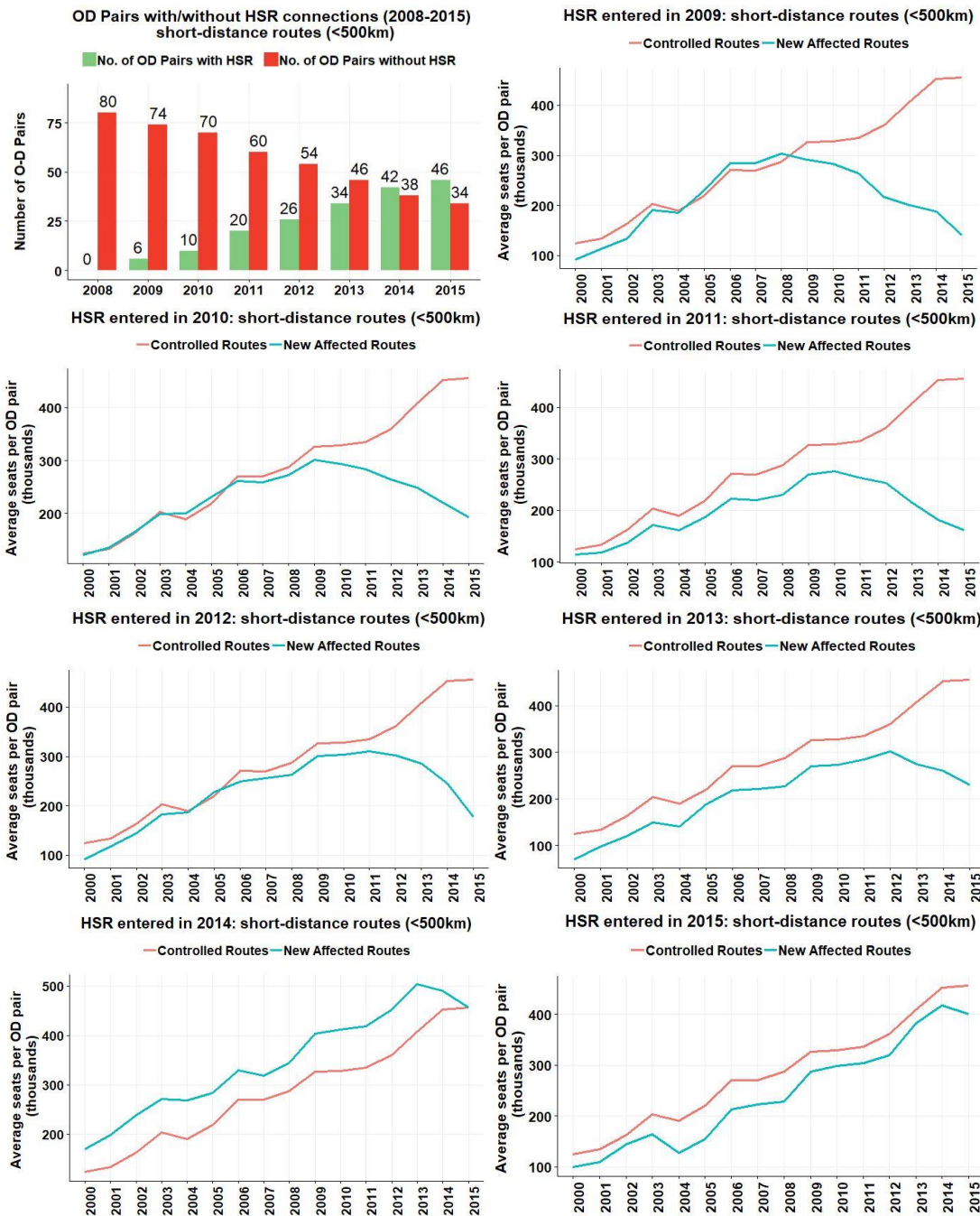


Figure 5-2. Air transport seat capacity of the control routes and routes affected by HSR entries in each year between 2009 and 2015, short-distance range.

Figure 5-2 firstly shows the number of short-distance O-D pairs with and without HSR connections between 2008 and 2015 (upper left). As can be seen, in total there are 80 city pairs in the sample belonging to the short-distance group, among which the number of affected O-D pairs increases from zero in 2008 to 46 in 2015; correspondingly, the number of controlled routes decreases from 80 to 34. As discussed earlier, by distinguishing O-D pairs with/without HSR on a year-by-year basis, city pairs that are newly connected by HSR in each year are identified and moved from the “controlled group” to the “affected group”. Therefore, the average seat capacity of these “new” affected routes connected by HSR in 2009, 2010, and 2011, etc. are compared against the controlled group separately, as shown in Figure 5-2. For example, it is found that HSR entered 10 new short-distance O-D pairs in 2011, which is the year that has the greatest increase in the number of new HSR connections. Thus, the green line in the chart titled “HSR entered in 2011” represents the average airline seat capacity of these 10 O-D pairs between 2000 and 2015. On the other hand, the red line represents the average seat capacity of the controlled group. Notably, as the number of O-D pairs without HSR varies year-by-year, for years before 2009, the average seat capacity is calculated as the total seat capacity of the 80 unaffected city pairs divided by 80, whilst the average seat capacity in 2009 is calculated as the 74 unaffected city pairs’ total capacity divided by 74, and the average seat capacity in 2010 is calculated as the 70 unaffected city pairs’ total capacity divided by 70, etc.

This year-by-year matching approach provides a transparent comparison of the historical average capacity trends between O-D pairs with and without HSR competition. It shows that, on the short-distance range, all the “new” affected routes in the “pre-HSR era” has very similar trends to the controlled routes. However, since the year that HSR entered the market, the average seat capacity of the new affected

routes generally starts a continuous decline (again, for routes where HSR enters in the fourth quarter of the year, the “effective” entry year is consider as one year after the actual entry), gradually diverting significantly from that of the controlled routes. Notably, airlines do not seem to dramatically reduce their seat capacity right after the HSR entries; rather, the reduction deepens year-after-year as airlines realise that their market share is increasingly taken by HSR on the short-distance markets. This observation is in line with the “lagged response” of travel behaviour (Tsai et al., 2014).

Table 5-1. Results of the *t*-test on annual growth rates of average seat capacity in affected and controlled O-D pairs, short-distance (< 500 km) routes.

<i>HSR Entry Year</i>	Phase	Mean affected growth	Mean controlled growth	Diff.	<i>t</i> -stat	<i>p</i> -value
<i>Entered in 2009</i>	2000-08	0.169	0.126	0.043	0.793	0.442
	2009-15	-0.101	0.070	-0.171	-4.411	0.001
<i>Entered in 2010</i>	2000-09	0.108	0.118	-0.010	-0.231	0.821
	2010-15	-0.094	0.057	-0.151	-5.750	0.000
<i>Entered in 2011</i>	2000-10	0.097	0.107	-0.010	-0.223	0.826
	2011-15	-0.100	0.069	-0.169	-4.973	0.001
<i>Entered in 2012</i>	2000-11	0.122	0.099	0.023	0.485	0.633
	2012-15	-0.126	0.081	-0.206	-3.300	0.027
<i>Entered in 2013</i>	2000-12	0.137	0.098	0.039	0.783	0.443
	2013-15	-0.088	0.083	-0.171	-4.011	0.029
<i>Entered in 2014</i>	2000-13	0.089	0.100	-0.011	-0.315	0.755
	2014-15	-0.048	0.059	-0.107	-1.957	0.249
<i>Entered in 2015</i>	2000-14	0.118	0.101	0.017	0.370	0.715
	2015-15	-0.041	0.008	-0.049	-1.128	0.321

To statistically examine the observations from Figure 5-2, a Welch Two Sample *t*-test was conducted on the annual growth rates of average seat capacity per O-D pair between the “new” affected routes and the controlled routes over the “pre-HSR” and “post-HSR” era. If there are no statistically significant differences in the

growth rates between the new affected routes and the controlled routes, they could be considered follow the common capacity growth, and vice versa.

It is found in Table 5-1 that, across all HSR entry years, at the “pre-HSR” phase the hypothesis that the true difference between the controlled routes and the affected routes in the mean of average seat capacity growth is equal to zero cannot be rejected at 5% statistically significant level; in comparison, this hypothesis is rejected at least at the 5% statistically significant level at the “post-HSR” phase (except for the 2014 and 2015 entries due to too few observations to compare). In addition, the mean affected growth after HSR entries are all negative, compared to the positive mean growth of the controlled routes at the “post-HSR” phase. Therefore, this test statistically demonstrates what Figure 5-2 depicts: (i) on the short-distance routes, airline supply started to gradually decline since the year that HSR entered the market, hence the growth rates of average seat capacity become negative; (ii) after HSR entries, the growth rates of airline seat capacity on the affected routes become statistically significantly different from those of the controlled routes.

Using the same approach, Figure 5-3 shows the comparison of historical average seat capacity for the medium-distance routes (500-1,000 km). Firstly, among all 344 medium-distance O-D pairs, the number of affected pairs increases rapidly from only 4 in 2009 to 258 in 2015. This is a result of more completed HSR corridors intersecting with each other and therefore many medium-distance city pairs are connected by the crossline HSR corridors. Furthermore, compared to a continuous seat capacity decline after the HSR entries on the short-distance routes (Figure 5-2), the seat capacity of medium-distance affected routes at the “post-HSR” phase seems to either have smaller growth or to stop the increasing trend, closer to be levelling off .

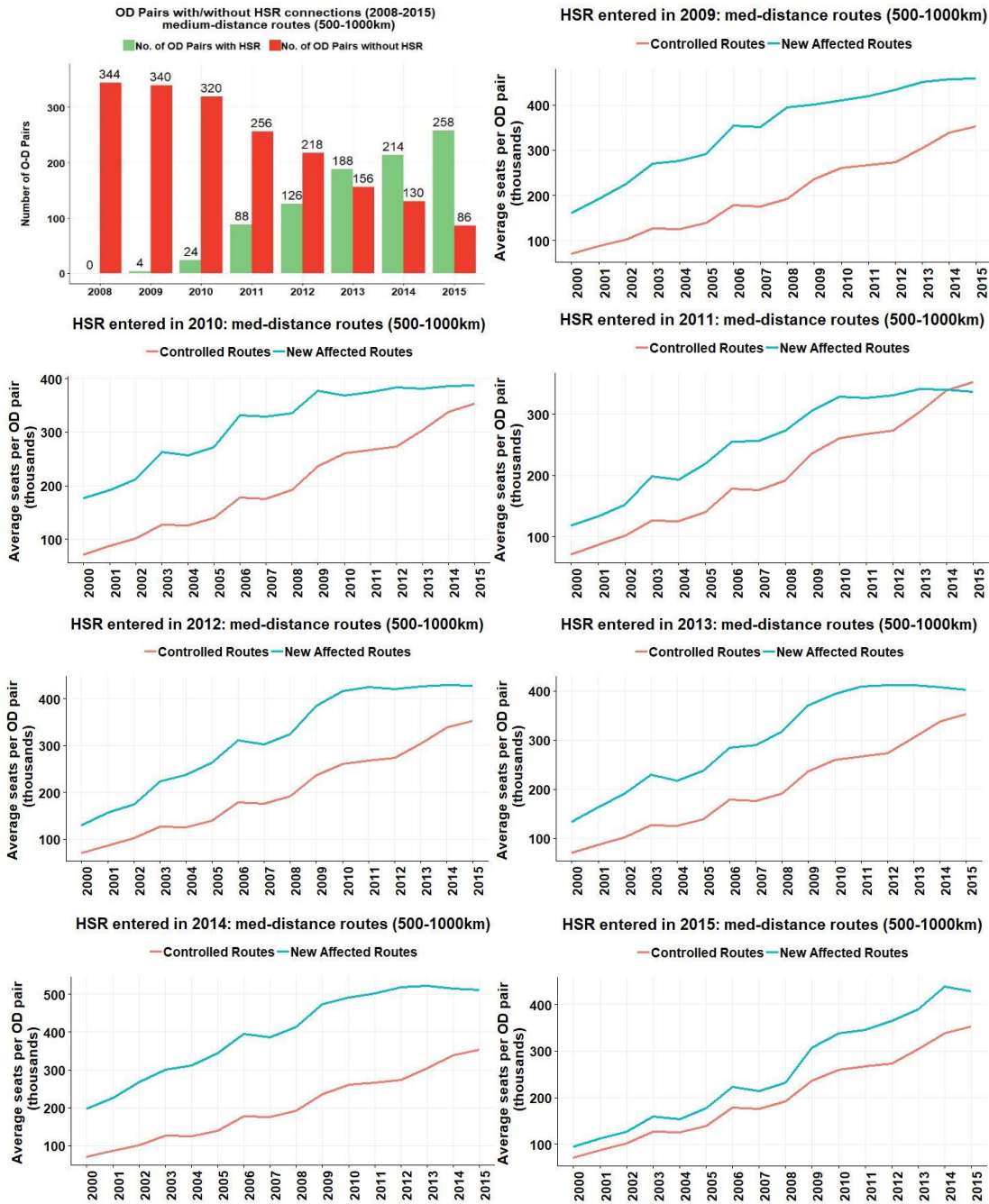


Figure 5-3. Air transport seat capacity of the control routes and routes affected by HSR entries in each year between 2009 and 2015, medium-distance range.

Figure 5-3 indicates that HSR may have less effects on airline supply over the medium-distance routes, compared to the short-distance routes. In order to test this hypothesis statistically, again the Welch Two Sample *t*-test was conducted to compare the annual capacity growth rates of the new-affected and the controlled routes before and after HSR entries. Table 5-2 shows the results of the *t*-test.

Table 5-2. Results of the *t*-test on annual growth rates of average seat capacity in affected and controlled O-D pairs, medium-distance (500-1000 km) routes.

<i>HSR Entry Year</i>	Phase	Mean affected growth	Mean controlled growth	Diff.	<i>t</i> -stat	<i>p</i> -value
<i>Entered in 2009</i>	2000-08	0.121	0.136	-0.015	-0.303	0.767
	2009-15	0.022	0.093	-0.071	-2.563	0.041
<i>Entered in 2010</i>	2000-09	0.092	0.147	-0.055	-1.144	0.270
	2010-15	0.005	0.070	-0.065	-3.345	0.014
<i>Entered in 2011</i>	2000-10	0.111	0.142	-0.031	-0.713	0.485
	2011-15	0.005	0.063	-0.058	-2.655	0.044
<i>Entered in 2012</i>	2000-11	0.116	0.132	-0.016	-0.370	0.716
	2012-15	0.002	0.073	-0.071	-2.893	0.047
<i>Entered in 2013</i>	2000-12	0.102	0.123	-0.021	-0.052	0.610
	2013-15	-0.008	0.090	-0.098	-4.105	0.041
<i>Entered in 2014</i>	2000-13	0.080	0.122	-0.042	-1.286	0.213
	2014-15	-0.011	0.077	-0.088	-2.489	0.091
<i>Entered in 2015</i>	2000-14	0.121	0.121	0.000	-0.014	0.989
	2015-15	-0.002	0.042	-0.040	-1.228	0.207

Similar to the short-distance routes, at the “pre-HSR” phase the hypothesis of equal mean of seat capacity growth between the two groups cannot be rejected at 5% statistically significant level; in comparison, this hypothesis is generally rejected at the 5% level for the “post-HSR” phase, albeit with slightly smaller *t*-statistics compared to the short-distance tests (Table 5-1). However, an important difference is that, at the “post-HSR” phase, the mean growth rates of the affected routes on the medium-distance range are mostly very close to zero, compared to the negative mean affected growth on the short-distance routes. This result suggests that, the competition effect of HSR on the medium-distance routes less strong than on the short-distance routes. Compared to the seat reduction on the short-distance routes, the minor impact of HSR on these medium-distance city pairs only makes airlines not add new seat capacities.

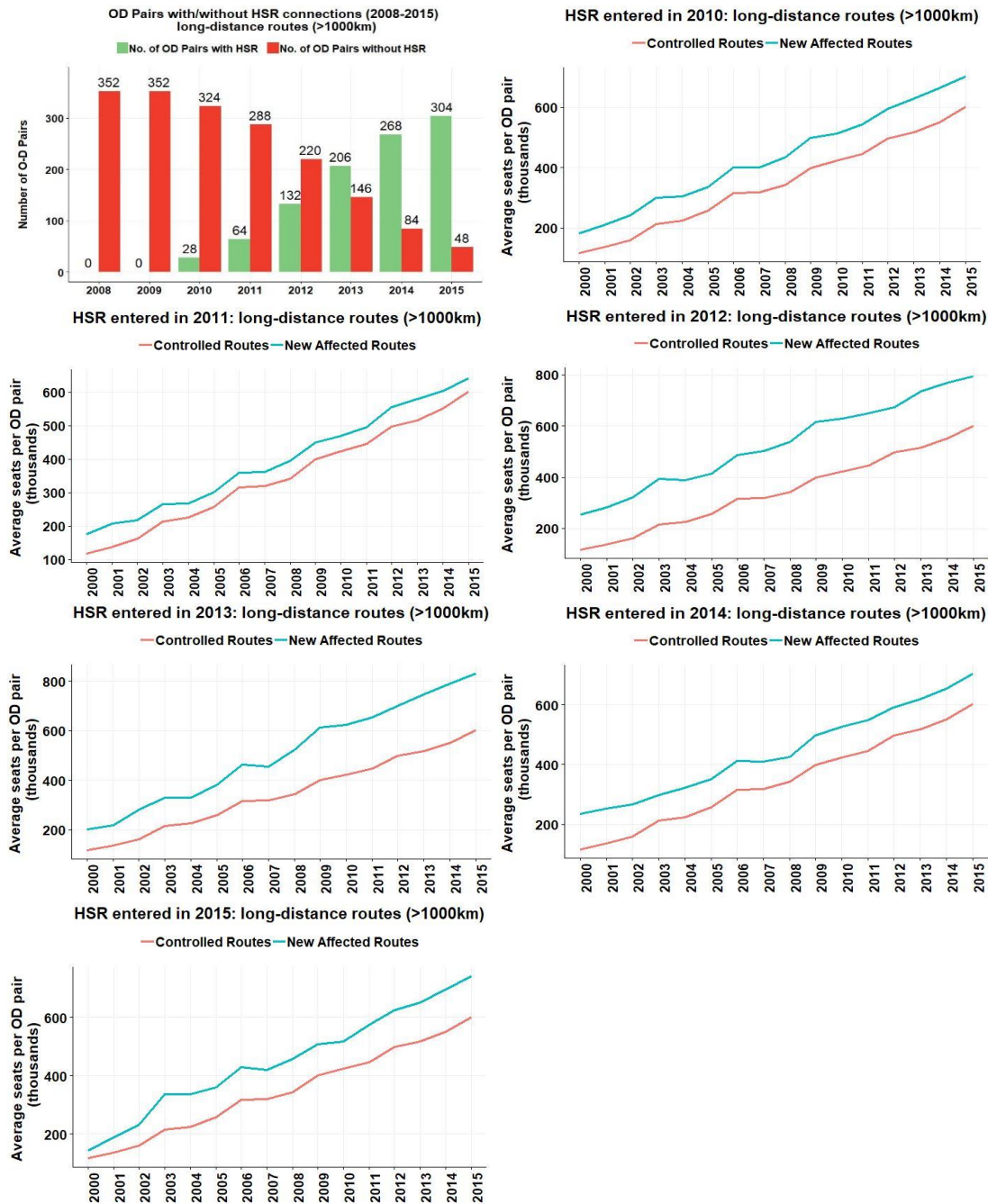


Figure 5-4. Air transport seat capacity of the control routes and routes affected by HSR entries in each year between 2009 and 2015, long-distance range.

Lastly, Figure 5-4 depicts the historical seat capacity trends on the 352 long-distance routes (> 1,000 km) covered by the sample. As can be seen, although there was no long-distance O-D pairs connected by HSR until 2010, the number of the affected long-distance routes has increased rapidly from 28 in 2010 to 304 by the end of 2015. The historical evolution of seat capacity on the long-distance affected and the

controlled routes shows similar trends across all HSR entry years, indicating that HSR may barely have any competition effects on airline supply over the long-distance routes. The Welch Two Sample *t*-test results shown in Table 5-3 confirm this observation: unlike the test results of short- and medium-distance routes, on the long-distance routes the hypothesis of equal mean of seat capacity growth between the affected and the controlled routes cannot be rejected at the 5% level for neither the “pre-HSR” phase nor the “post-HSR” phase. Therefore, it could be concluded that, over long-distance range, the affected routes have a common trend in seat capacity with the controlled routes both before and after the HSR entries.

Table 5-3. Results of the *t*-test on annual growth rates of average seat capacity in affected and controlled O-D pairs, long-distance (>1000 km) routes.

<i>HSR Entry Year</i>	Phase	Mean affected growth	Mean controlled growth	Diff.	<i>t</i> -stat	<i>p</i> -value
<i>Entered in 2010</i>	2000-09	0.121	0.149	-0.028	-0.678	0.508
	2010-15	0.058	0.071	-0.013	-0.874	0.405
<i>Entered in 2011</i>	2000-10	0.107	0.141	-0.034	-0.864	0.400
	2011-15	0.065	0.073	-0.008	-0.411	0.692
<i>Entered in 2012</i>	2000-11	0.111	0.133	-0.022	-1.152	0.264
	2012-15	0.051	0.078	-0.027	-1.213	0.272
<i>Entered in 2013</i>	2000-12	0.112	0.131	-0.019	-0.497	0.624
	2013-15	0.059	0.066	-0.007	-0.409	0.718
<i>Entered in 2014</i>	2000-13	0.078	0.124	-0.046	-1.586	0.129
	2014-15	0.067	0.079	-0.012	-0.845	0.504
<i>Entered in 2015</i>	2000-14	0.126	0.121	0.005	0.141	0.889
	2015-15	0.063	0.092	-0.029	-1.128	0.212

In addition to the above findings with respect to the HSR competition effects on airline seat capacity before and after HSR entering short-, medium-, and long-distance routes, there are a few other issues worth exploring.

First of all, on the short-distance routes (see Figure 5-2), there seem to be a levelling-off growth in seat capacity between 2009 and 2011 on routes that are not (yet) affected by HSR. The levelling off may have reflected a change in government policy, an overall airline capacity constraint, or an economic slowdown. Having investigated in the potential reason of this phenomenon, I did not find any government policies that may lead to this levelling off on the airline seat capacity. Furthermore, there is also no evidence of an overall airline capacity constraint. In fact, according to China's Statistics Yearbook (2009-2012), the number of passenger aircraft owned by Chinese airlines experienced a steady growth during this period: 1297 in total in 2009 (with 593 B737s and 219 A320s), 1453 in 2010 (with 650 B737s and 281 A320s), and 1601 in 2011 (with 700 B737s and 357 A320s). Finally, if it is caused by an economic slowdown, one would also expect the same flattened growth between 2009 and 2011 on the medium- and long-distance routes, which would then suggest that the entire airline market in China were less active during this period. However, such levelling off is not found in the medium- and long-distance routes between 2009 and 2011; on the contrary, airline seat capacity experienced a relatively fast increase on the medium- (Figure 5-3) and long-distance (Figure 5-4) routes during this period. As a result, a more plausible explanation for the levelling off during this period on the short-distance routes is that airlines temporarily adjusted their fleet distribution and moved some extra capacity that could have been added to the short-distance routes to the medium- and long-distance routes instead.

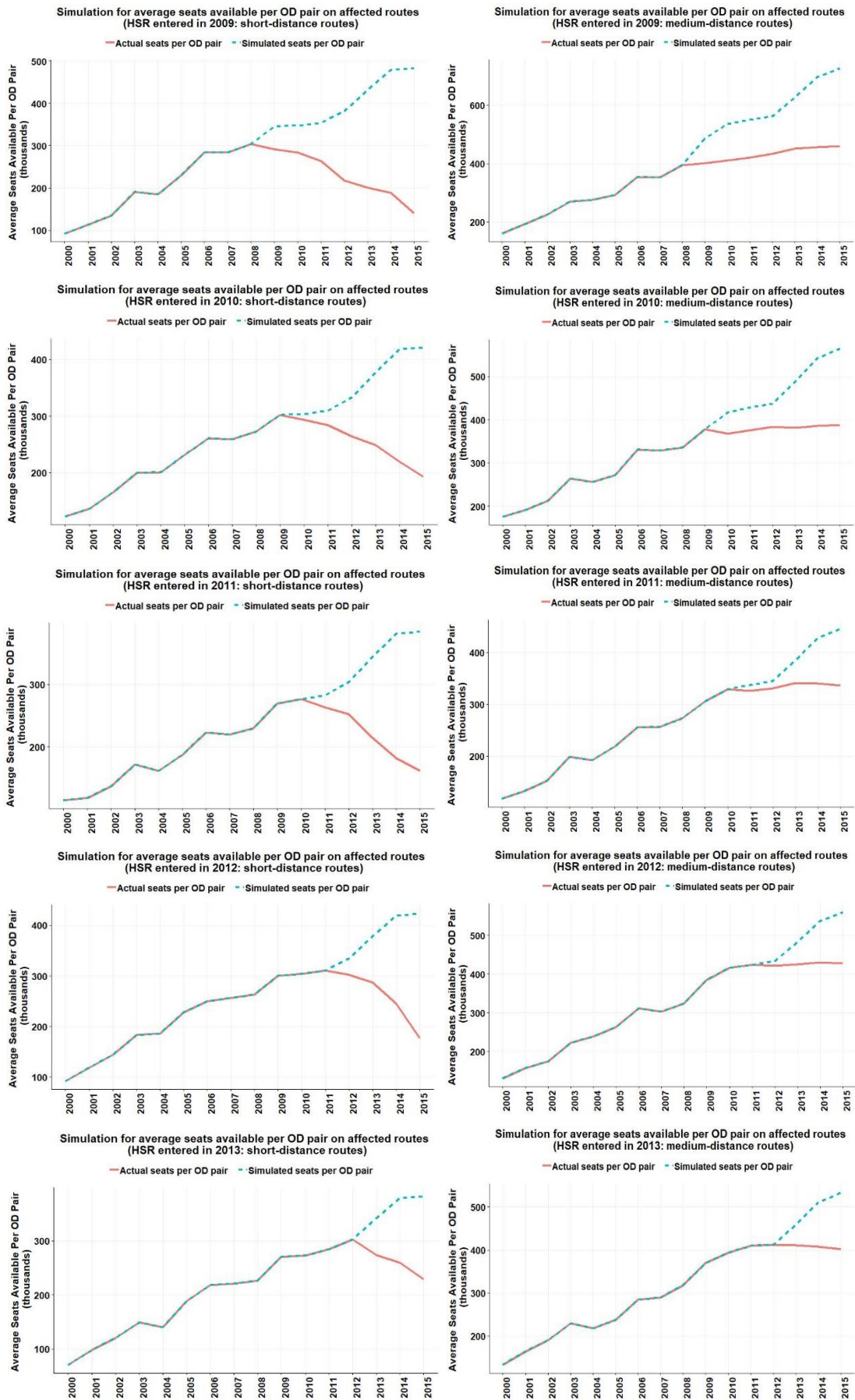
Secondly, Figure 5-2 also shows a rapid increase in airline seat capacity on the controlled routes from 2011. This might be a result of the arrival of new aircraft. Based on China's Statistics Yearbook (2012-2015), compared to the increase in the number of aircraft in the domestic Chinese market in previous years, i.e. 156 new aircraft from

2009 to 2010, and 148 new aircraft from 2010 to 2011, Chinese airlines saw an arrival of 177 new aircraft in 2012, 204 in 2013, and 225 in 2014. Thus, the arrival of more new aircraft could be the reason of the rapid increase in seat capacity on the controlled routes after 2011.

5.4 Estimation to the Reduced Airline Supply due to HSR

In order to estimate the possible reduction in seat capacity on the affected routes due to HSR competition, this section simulates the seat capacity on the affected routes, assuming no HSR were introduced. Seat reductions could be then estimated by taking the difference between the actual seat capacity and the simulated seat capacity on the affected routes.

Based on the *t*-test (Table 5-1 to 5-3) in the previous section, it can be inferred that, on the short- and medium-distance routes, if HSR were not introduced to the affected routes, seat capacity growth of the affected routes in the “post-HSR” years should have had no statistically significant difference to that of the controlled routes, just as the growth at the “pre-HSR” phase. Therefore, the annual growth rates of average seat capacity on the controlled routes are used to simulate a “without-HSR” capacity growth of the affected routes at the “post-HSR” phase. The differences between the actual and the simulated seat capacity could be considered as the reduced supply on the affected routes due to HSR competition. Figure 5-5 depicts the actual and the simulated airline seat capacity on the affected routes by each HSR entry year for the short- (left-hand side) and medium-distance (right-hand side) range.



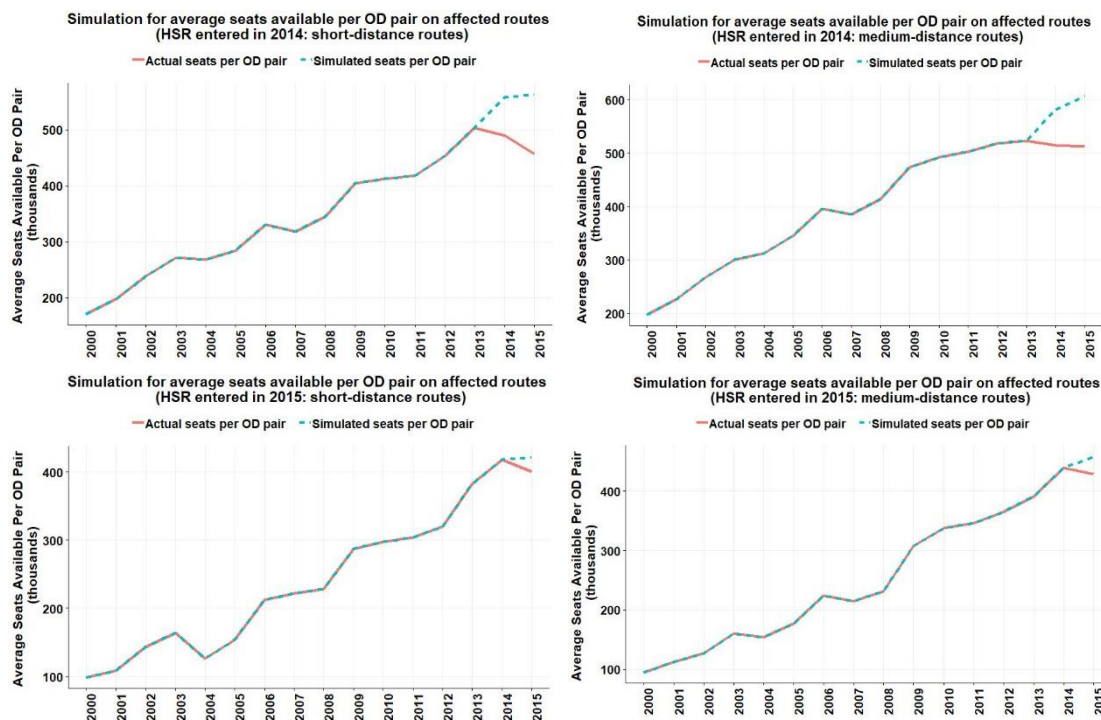


Figure 5-5. Simulated seat capacity on the short- and medium-distance affected routes between 2000 and 2015.

It can be seen from Figure 5-5 that the simulated average seat capacity, assuming HSR were not introduced, is larger than the actual capacity on the affected routes during the “post-HSR” years. Thus, this simulated growth of seat capacity could be considered as the “counterfactual” growth of the affected routes. Furthermore, the reduction in seat capacity in a given year is calculated from the difference in the average seat capacity per O-D pair between the actual and the simulated seat capacity, multiplied by the number of new affected city pairs that HSR connected in that year.

It is estimated that, between 2009 and 2015, the average airline seat capacity reduction on the short-distance routes is about 89,408 per O-D pair per year, and the medium-distance routes is around half of this level at about 42,823 per O-D pair per year. Thus, HSR entries may, on average, lead to more significant drop in airline seat capacity on the short-distance routes than the medium-distance routes.

5.5 Operational Net CO₂ Emissions Savings

Having estimated the possible reduction in seat capacity on the affected routes due to HSR competition in the previous section, this section calculates net savings of CO₂ emissions that may have already been achieved from substituting HSR for air transport at operational phase. Following that, a sensitivity analysis is conducted to estimate emissions savings under a low-carbon power generation mix. Results of the sensitivity analysis are compared against the historical emissions savings to illustrate the potential for greater emissions reduction of air transport from mode substitution, if China had a cleaner energy mix for electricity generation over the same period.

5.5.1 CO₂ Emissions Calculation

In order to estimate the net CO₂ emissions savings that China has achieved from HSR substitution for air transport at operational phase, both the gross reduction of emissions from the diverted aviation demand and the emissions generated by HSR for carrying the shifted demand from aviation need to be calculated.

Air transport Operational Emissions

Aircraft fuel burn on a given flight segment is determined by aircraft type and size class, load factor, stage length, and total number of flights for each aircraft type operated. In this study, fuel burn is calculated using the PIANO-X aircraft performance model (Lissys Ltd, 2017) for taking off, climbing, cruising, descending, landing, and taxing. CO₂ emissions are obtained by multiplying the amount of fuel consumed with emissions factor at 3,120gCO₂/kg fuel burn. Notably, the CO₂ emissions estimated by the PIANO-X is just for aircraft operation. The gross reduction

of CO₂ emissions from aviation is calculated based on the reduced airline seat capacity estimated in the previous section.

HSR Operational Emissions

In this study, HSR emissions are calculated just for the estimated traffic shifted from air transport to HSR. Thus, any induced demand or transitioning inter-city travels from other transport modes are not included in the calculation. The historical energy mix for electricity generation in China from 2009 to 2015 is obtained from International Energy Agency (IEA, 2018) and shown in Figure 5-5. Figure 5-5(a) shows that, during this period, coal still plays a dominant role in China's electricity production, although its proportion has been slowly decreasing due to its replacement by nuclear and renewable sources, such as hydro, wind, and solar. The historical emission factors of each energy source in power generation shown in Figure 5-2(b) are obtained from IEA (2017b).

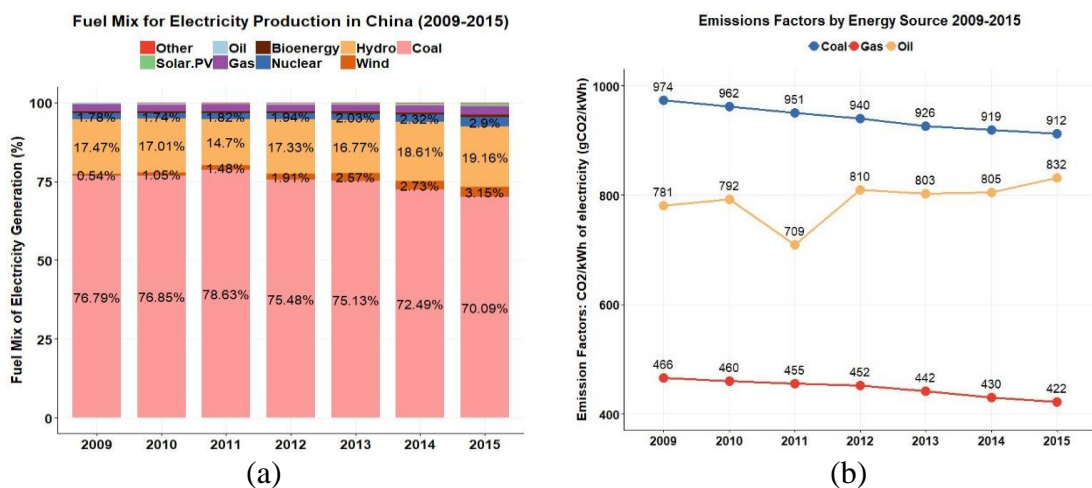


Figure 5-6. (a) China's electricity generation mix and (b) corresponding emission factors of fossil fuel energy sources, 2009-2015.

Given that CO₂ emissions of HSR from power plant is determined by type of fuel used for electricity generation, the fuel mix is explicitly addressed in calculating HSR emissions from power plants, as shown in Eq. (5-1) :

$$\begin{cases} ElectricityUse_{HSR} = Electricity.Intensity_{HSR} \times Seat.km_{od} \times Trains_{od} \\ CO_{2HSR} = \sum(ElectricityUse_{HSR} \times \left(\frac{Gen_S}{Gen_T}\right)_Y \times EF_{S,Y}) \end{cases} \quad (5-1)$$

Where:

- $ElectricityUse_{HSR}$: kWh of electricity consumption by HSR operating between origin city o and destination city d ;
- $Electricity.Intensity_{HSR}$: kWh of electricity consumed per HSR seat-kilometre;
- $Trains_{od}$: number of trains operated between origin city o and destination city d in the given year;
- $\left(\frac{Gen_S}{Gen_T}\right)_Y$: Share of source S in the electricity generation in China in year Y ; Gen_S is the total electricity generation (GWh) from source S , and Gen_T is the total generation of electricity (GWh) from all sources;
- CO_{2HSR} : CO₂ emissions generated by HSR from power generation at power plants;
- $EF_{S,Y}$: Emission Factors of source S in the fuel mix of electricity generation in year Y .

This chapter computes HSR emissions specifically in China's HSR context. Four main types of high-speed trains are used in the Chinese HSR system, namely CRHA Series, CRHB Series, CRH380 Series, and CRH380L Series (Zhou, 2014). Although there are currently no data for the electricity intensity of China's HSR trains, such data is available for their prototypes (Chester & Horvath, 2012, SI), from which the CRH vehicles inherit almost the same structure and vehicle materials (Yue et al., 2015). Thus, the electricity intensity values of these prototypes are used to compute the energy use of China's HSR.

In order to minimize effects on the calculation of the potential variation in energy efficiency of these derivatives from their prototypes, a generic model is also included, which has an electricity intensity value averaged across a range of HSR

electricity intensity values summarized by Chester and Horvath (2012). Table 5-2 summarizes the key features of the CRH vehicles based on Zhou (2014) and Chester and Horvath (2012). Taking the estimated reduction in airline seat capacity on the affected routes, as well as the annual average airline load factor, total passengers shifted to HSR can be estimated, upon which the reduced CO₂ emissions of air transport resulted from the effects of HSR substitution could be calculated.

Table 5-4. Key parameters of China’s CRH series trains.

Vehicle Type	Prototype	Electricity Intensity (kWh/seat-km)	Seat capacity	Max speed (km/h)	Train length (m)	Weight (ton)	Train sets
CRHA	Shinkansen E2-1000	0.037	660	250	213.5	420.4	8
CRHB	Siemens Bahn ICE-3	0.058	1,230	250	426.3	690.0	16
CRH380	Shinkansen E2-1000	0.037	556	380	215.3	399.0	8
CRH380L	Siemens Bahn ICE-3	0.058	1,061	350	399.3	890.0	16
Generic Model	Average of all HSR vehicles	0.043	N/A	N/A	N/A	N/A	N/A

5.5.2 Historical Net CO₂ Emissions Savings

Net CO₂ emissions savings at operational phase are calculated from the gross reduction of aviation emissions and the additional HSR emissions due to the diverted demand from air transport. As mentioned earlier, the reduced CO₂ emissions from air travel are considered as the difference between emissions from observed airline supply and emissions from the simulated supply, assuming no adoption of HSR. The additional HSR emissions are estimated based on Eq.(5-1), where the number of trains for transporting the diverted demand from aviation are estimated with an assumed average capacity utilization of 70% (Yue et al., 2015). As mentioned previously, given that the electricity intensity of China’s CRH trains are uncertain, the historical emissions savings are estimated based on 1) electricity intensities of CRH prototypes

(TYPE 1), and 2) the average electricity intensity value of a generic CRH model (TYPE 2) (see Table 5-2). Figure 5-6 depicts the estimations of possible historical emissions savings between 2009 and 2015, depending on the assumptions of the CHR's electricity intensity.

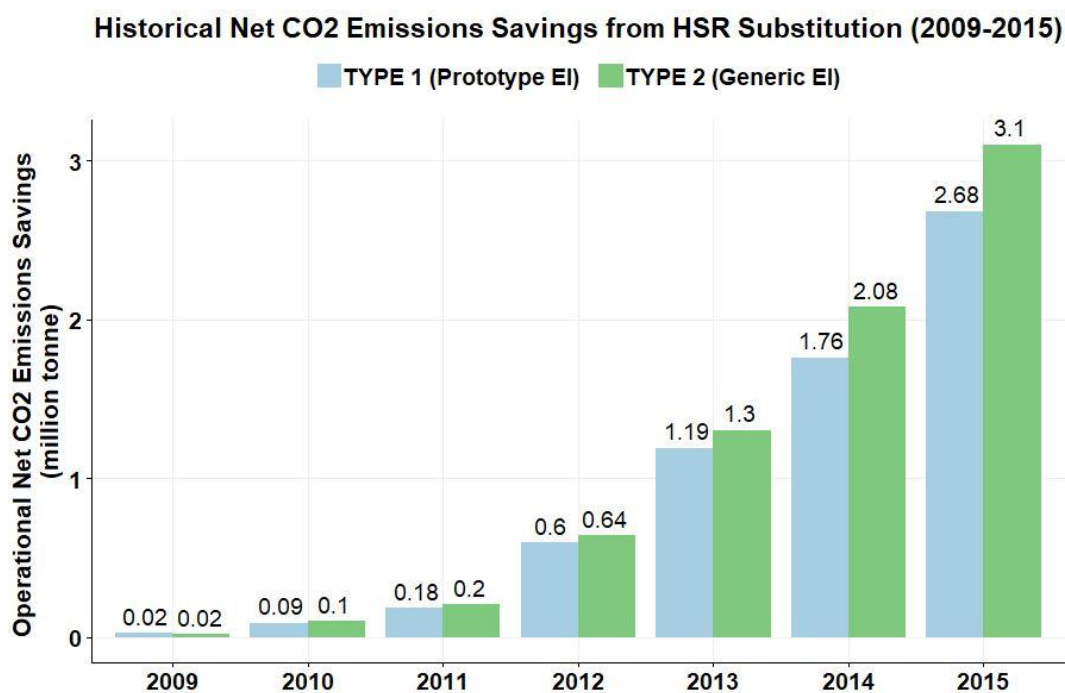


Figure 5-7. Historical net CO₂ emissions savings from HSR substitution, based on assumptions on CRH's electricity intensity (2009-2015).

As shown in Figure 5-6, overall, the cumulative historical emissions savings between 2009 and 2015 from HSR substitution for air transport is about 6.52-7.44 MtCO₂. This was equivalent to 12–14% of the 53.8 million tonne domestic aviation emissions in China in 2015. Assuming the CHR trains have a generic electricity intensity at 0.043 kWh/seat-km (see Table 5-2), the estimated emissions savings are slightly higher compared to those computed based on the electricity intensities of corresponding prototypes. This is potentially because more CRHB Series and CRH380L vehicles with higher electricity intensity (see Table 5-2) are used on long-haul routes, which produce more emissions than the generic HSR model with a lower electricity intensity.

Specifically, substituting HSR for air transport before 2012 could save just 0.29–0.32 MtCO₂ in total, as only a few O-D pairs were connected by HSR on the short- and medium distance before 2012 and thus the HSR substitution effect was relatively small. As the HSR network expands, more passengers may have shifted from air transport to HSR, resulting in an increase in net emissions savings. In 2012 the total net savings more than tripled compared to the previous year, increasing to 0.6–0.64 Mt. Since 2012, the estimated net emissions savings see a rapid increase, reaching 2.68–3.1 MtCO₂ in 2015, which accounts for about 5-6% of the total 53.8 million tonnes domestic aviation emissions in that year.

5.5.3 Sensitivity Analysis for Emissions Savings under Low-Carbon Power Generation

Compared against the estimated historical savings, this section conducts a sensitivity test for a “low-carbon” power generation to examine how much additional emissions savings would substituting HSR for air transport generate, if China had a cleaner power generation sector compared to its observed energy mix between 2009 and 2015 (Figure 5-5).

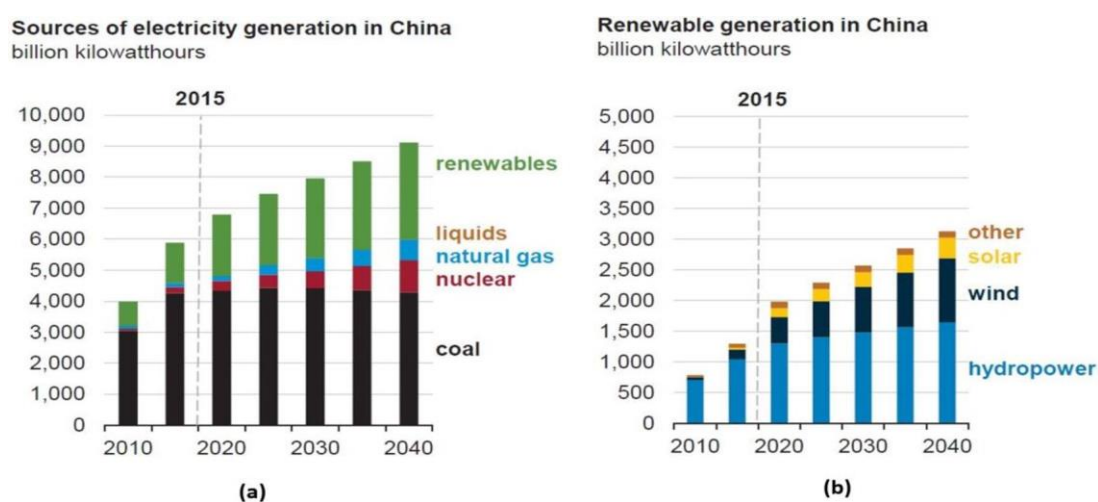


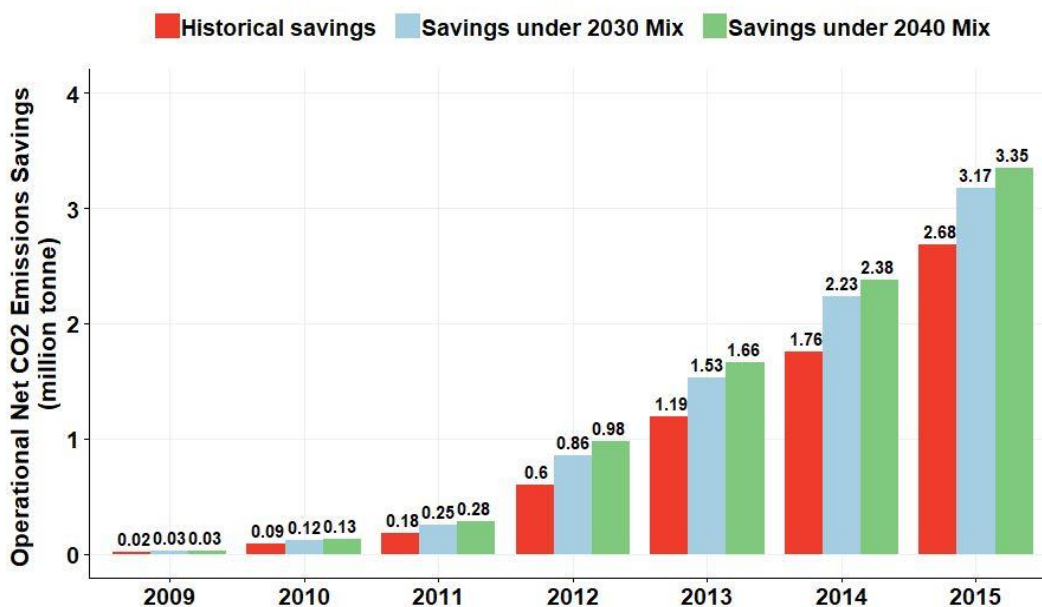
Figure 5-8. EIA projections on China's energy mix for electricity generation (2010-2040): (a) sources of power generation, and (b) renewable sources mix.

The lower carbon intensity power generation mix is obtained from the U.S. Energy Information Administration (EIA, 2018), which projects China's possible energy mix based on the country's climate change pledge in the Paris Agreement. As shown in Figure 5-7. EIA (2018) projects that, by gradually displacing coal with renewables, nuclear, and natural gas, the share of coal in total electricity generation will drop from 70% of the 2015 level (Figure 5-5) to 55% in 2030 and to 47% in 2040. Meanwhile, the shares of renewables continues to increase, with annual growth rates between 2015 and 2040 at 7% in solar PV and 5% in wind. In addition, the share of nuclear generation increases from 3% in 2015 to 11% in 2040, and over the same period, the share of natural gas is expected to increase from 2% to 7%.

Using the EIA's projection, this sensitivity analysis estimates HSR emissions between 2009 and 2015 for transporting the diverted demand from aviation, assuming China had a cleaner energy mix that is same to the projected 2030 and 2040 power generation over this period. By comparing this "what-if" test with the actual emissions savings, this section demonstrates the importance of decarbonizing China's fuel mix in electricity generation and the knock-on benefits for the transport sector. Figure 5-8 depicts the estimation results of the sensitivity analysis, compared against the historical emissions savings estimated in the previous section. Same to Figure 5-6, emissions savings under a cleaner power generation sector are calculated based on 1) electricity intensities of CRH prototypes (TYPE 1), and 2) the average electricity intensity value of a generic CRH model (TYPE 2), respectively.

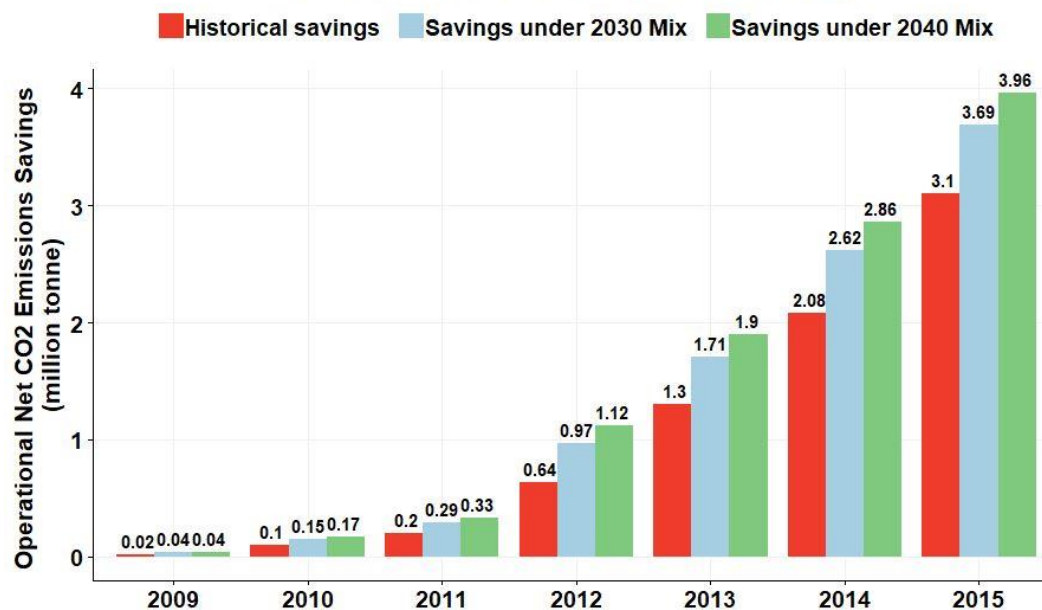
Figure 5-8 shows the results of the sensitivity test with the electricity intensities of corresponding CRH's prototypes (Figure 5-8, a) and with the generic electricity intensity (Figure 5-8, b) (see Table 5-2). In both figures, a cleaner energy mix for power generation could produce more emissions savings compared to the actual case.

**Net CO2 Emissions Savings under Clean Power Generation (2009-2015)
(TYPE 1: with Prototype Electricity Intensity)**



(a)

**Net CO2 Emissions Savings under Clean Power Generation (2009-2015)
(TYPE 2: with Generic Electricity Intensity)**



(b)

Figure 5-9. Results of the sensitivity tests for emissions savings under clean power generation in China (2012-2015).

As can be seen, under the 2030 power generation mix (blue bars), compared to the historical savings (red bars), the accumulative emissions savings from TYPE 1 HSR substitution (Figure 5-8a) are about 8.19 Mt, indicating 1.67 MtCO₂ additional

emissions savings; In comparison, the accumulative emissions savings from TYPE 2 HSR substitution (Figure 5-8b) are about 9.47 Mt, thus 2.95 Mt additional emissions savings. However, under the 2040 energy mix (green bars), the accumulative emissions savings are 8.81-10.38 Mt, hence the additional savings from the 2030 mix to the 2040 mix are just 0.62-0.91 Mt. This is because with the 2030 energy mix, the share of coal is already reduced from 70% of the observed level (Figure 5-5) to 55% (Figure 5-7a) in its electricity generation sector. As a result, the benefits of continuing decarbonizing China's energy mix to the 2040 level yield smaller increase of savings. This suggests that although reducing the carbon intensity of electricity generation from today's level will result in considerable and immediate improvement of emissions reduction, such potential will probably reach a limit. Nevertheless, decarbonizing power generation remains the most important pathway of increasing emissions savings from HSR substitution for air transport in China.

5.6 Conclusions

The analysis in this chapter estimates that China's HSR infrastructure has led to emissions savings of 6.52-7.44 million tonnes of CO₂ from substituting HSR for air transport over the period of 2009 to 2015. This was equivalent to about 12–14% of the 53.8 million tonne domestic aviation emissions in China in 2015. It is statistically demonstrated that, from the year that HSR entered the market airlines have reduced their seat capacity on the short- (less than 500 km) and stopped adding more capacity on the medium-distance (500-1,000 km) routes. Thus, the HSR competition effects are found to be stronger on the short-distance routes than the medium-distance routes. In

contrast, on the long-distance (more than 1,000 km) O-D pairs, the growth of airline seat capacity does not seem to be affected by HSR entries.

Through a sensitivity analysis, this chapter highlights that a low-carbon power generation sector could have provided considerable additional emissions savings over the same period. Since China relies heavily on coal in its electricity generation, with the current energy mix, HSR still has great potential to reduce its CO₂ emissions even further if China gradually displaces coal by nuclear and renewable energy sources. The sensitivity analysis demonstrates that by just maintaining an energy mix with the share of coal at 55% (compared with 70% in 2015), in total the HSR substitution for aviation could have achieved 1.67-2.95 million tonnes additional emissions saving compared to those observed.

This chapter attempted to estimate the impacts of HSR substitution from supply data for comparing growth rates and forecasting trends. The robustness of this approach could be potentially improved through the use of discrete choice models to predict market shares of both HSR and air transport. Additionally, the calculation conducted in this chapter focuses only on the operational phase of air transport and HSR. Such calculation could be expanded to the lifecycle level. As a “carry-on” work of this topic, the next chapter will evaluate the potential of HSR substitution in a long-term future with both aspects described above addressed.

Chapter 6 Modelling Net Savings of China's Aviation Lifecycle CO₂ Emissions from High-Speed Modal Substitution

Since the onset of China's massive infrastructure investments in High-Speed Rail (HSR) in 2008, passenger mode choice for inter-city travel has experienced significant changes. Whereas Chapter 5 estimated the historical operational CO₂ emission savings from diverting air passengers to HSR, this chapter estimates the future lifecycle emissions savings from the planned enhanced HSR network. It first presents a city-pair demand model to project the demand for HSR and domestic aviation under the 2015 and the future planned 2025 HSR network, between 2015 and 2050. With the enhanced introduction of HSR in 2025, more air passengers could be diverted to HSR. A lifecycle assessment of both operational and non-operational (manufacture, maintenance, construction, and fuel production) emissions from the two transport modes is then conducted. The results show that, compared to the baseline 2015 network, the 2025 HSR network with a declining carbon intensity for power generation could generate cumulative net lifecycle emissions savings of 736-960 MtCO₂ from HSR substitution for air transport, depending on assumptions on future urban population, GDP per capita, and jet fuel prices in China. The annual average of this amount between 2016 and 2050 are equivalent to 39-50% of the 54 million tonnes domestic aviation CO₂ emissions in 2015.

6.1 Introduction

Driven by rapid economic growth, air transportation in domestic China has increased from 3.4 million passengers in 1980 to 394.1 million in 2015 (China Statistical Yearbook, 2016). According to Airbus (2017), air traffic of the domestic Chinese market could almost quadruple between 2016 and 2036 and become the world's largest air transport market with about 1,900 billion revenue passenger kilometres (RPK). However, the rapid increase in air transport demand comes at an environmental cost. In 2015, domestic passenger air transport generated 54 MtCO₂ emissions, thus accounting for 5.6% of total emissions from the transport sector in China (IEA, 2017). Because non-CO₂ warming impacts of aircraft are estimated to be of at least the same magnitude as the aircraft CO₂ emissions impact (Schäfer, et al. 2018; Lee, et al., 2009; Dorbian, et al. 2011; Brasseur et al., 2016), aviation has become a rising concern for climate change mitigation.

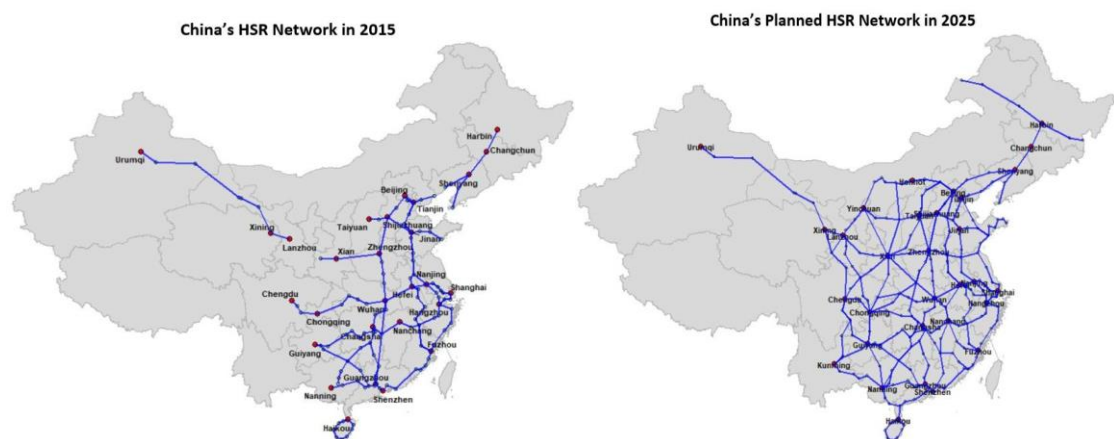


Figure 6-1. HSR network in China 2015 versus 2025.

Substituting flights by high-speed rail (HSR), which experiences a considerably lower energy intensity than air transport, could be an effective strategy for reducing domestic aviation emissions in China (Wang et al., 2019). Building upon

the initial infrastructure investments in 2008, China aims to further expand its HSR network from 19,838 km in 2015 to 38,000 km in 2025 (State Council, 2016, see Figure 6-1). This network expansion could lead to further reductions in aviation CO₂ emissions.

The next section of this chapter describes the data underlying this work and the econometric model developed in this study to project inter-city aviation and HSR demand. Following that, section 6.3 provides in-depth analysis on the estimation results of the demand model. Based on the model estimates, section 6.4 presents air demand projections under the 2015 and the future planned 2025 HSR network, between 2015 and 2050. Additional air transport capacity needed to meet the projected demand is also estimated. Finally, section 6.5 provides lifecycle assessments of CO₂ emissions from both transport modes. The associated net lifecycle CO₂ emissions savings are calculated from the “avoided” emissions in aviation and the additional emissions generated from transporting the shifted air passengers by HSR. Section 6.6 offers conclusions.

6.2 Data and Modelling Framework

6.2.1 Data

This chapter combines the origin-destination (O-D) city pair passenger flows for the Chinese domestic air transport and with HSR operations in 2015. Only cities with direct access to both transport modes are included. Data for air transport with respect to O-D city pair passenger demand, average airfares, airport-to-airport flight time, and flight frequency are obtained from the Sabre Market Intelligence dataset (Sabre, 2016). O-D passenger flows of HSR in 2015 are provided by the China

Railway Corporation (CRC). Data on HSR O-D journey time (station to station, in hours) and service frequency for all sample city pairs are collected from the official railway timetable in 2015. Average ticket prices of HSR are extracted from China's official rail ticket booking website (www.12306.cn) using the Python Beautiful Soup package and are converted into 2015 US dollars, adjusted firstly by inflation and then exchange rates (IMF, 2016). Given that the HSR ticket prices in China have remained constant over the past years (World Bank, 2019), the collected prices are expected to reflect the price levels in 2015. In addition, data on average driving time between city centres and the local HSR rail station and airport for all sample cities are also extracted from the Baidu map (<https://map.baidu.com>). Finally, the city-level demographic data on income per capita and total urban population in 2015 are collected from the Metropolitan Statistical Yearbook (NBS, 2016) for all sample cities. Based on the data described above, a demand forecasting framework is developed to project future aviation demand under the HSR competition.

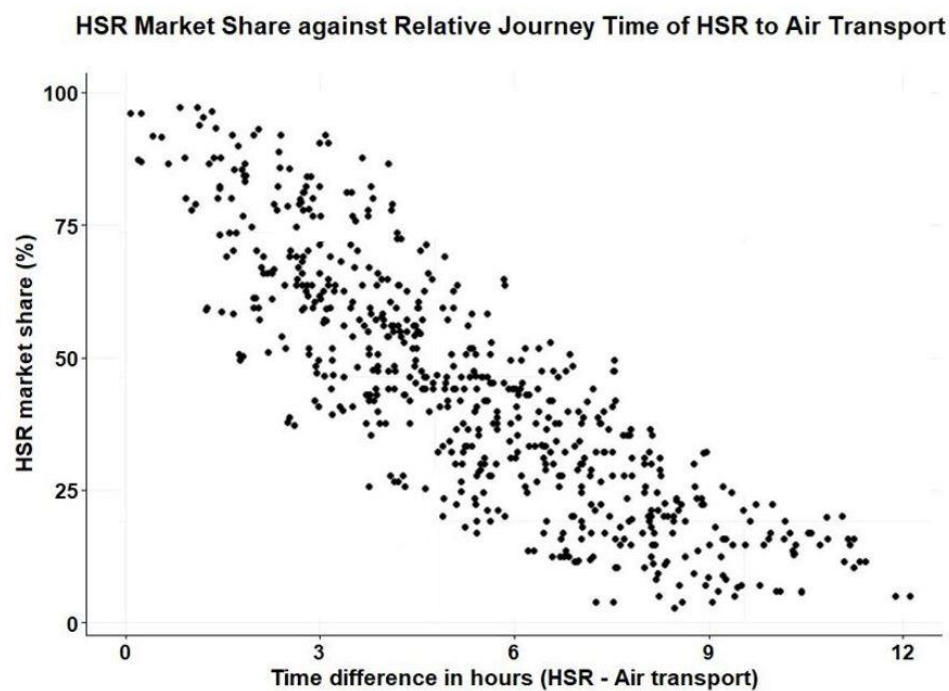


Figure 6-2. HSR passenger market shares against travel time difference (in hours) between HSR and air transport.

Given that the domestic Chinese air transport routes are dominated by a point-to-point network (Jiang and Zhang, 2016; Zhang, 2010; Fu et al. 2012), this study includes only O-D city pairs served by direct flights (accounting for 99.4% of domestic total enplanements and 99.1% of the domestic total RPK in 2015). In total, a dataset consisting of 608 city pairs from 45 Chinese major cities that are directly connected by both HSR and air transport is constructed. Figure 6-1 shows the HSR passenger market shares for the 608 city pairs against the relative journey time (in hours) of HSR (station to station) to air transport (airport to airport). As can be seen, the market share of HSR in competition with air travel resembles an *S*-curve which declines as the time difference between HSR and air transport increases. HSR is the preferred transport mode when the time difference to air travel is no more than 3 hours. The competition between the two transport modes becomes more intense on the 3-9 hours' time difference interval. In contrast, when HSR travel takes an additional 9 hours compared to air travel, air transport typically takes at least 75% of the market. Thus, aviation is still dominating long-haul travel due to its clear advantage in travel time.

6.2.2 Modelling Framework

This study adopts the modelling approach used by Jamin et al. (2004) who estimated air passenger flows for the domestic U.S. market through combining a gravity model for total trip demand and a mode choice model for air and automobile transport. Similar to Jamin et al. (2004), this study specifies a gravity model for total passenger demand of HSR and air transport in each city pair in Eq. (6-1) as a function of the socioeconomic characteristics of city i and city j , including their population size P and income I , and an expression specifying the characteristics of the two transport modes (HSR and aviation) operating between them. In addition, a variable that reflects

city special attributes, i.e. whether they are business activity centres or tourism destinations, is also included. The total travel demand is then distributed to HSR and air travel using a binary logit model, which represents the mode choice for the two competing transport modes, as shown in Eq.(6-2). The utility functions for air travel and HSR are specified in Eq.(6-5) and (6-6). Based on the logit model, demand of air travel under the HSR competition is derived in Eq.(6-3), which is the product of total (air and HSR) passenger demand D_{ij} from Eq.(6-1) and the mode share of air travel, i.e., the probability of passengers choosing air transport over HSR from Eq.(6-2). Eq.(6-4) is the “logsum” term (Ben-Akiva and Lerman, 1985) that represents the consumer surplus of travel between the city pairs.

$$D_{ij} = K(P_i P_j)^\alpha (I_i I_j)^\beta e^{\delta \cdot SpecBoth_{ij}} e^{\vartheta \cdot SpecNeither_{ij}} e^{\psi \cdot L_{ij}} \quad (6-1)$$

$$S(Air|ij) = \frac{e^{U_{Air}}}{e^{U_{Air}} + e^{U_{HSR}}} \quad (6-2)$$

$$D_{ij(Air)} = D_{ij} S(Air|ij) + E \quad (6-3)$$

$$L_{ij} = \ln(e^{U_{HSR}} + e^{U_{Air}}) \quad (6-4)$$

$$U_{HSR} = \beta_{HSR} + \beta_1 Cost_{HSR} + \beta_2 Time_{HSR} + \beta_3 \ln(FreqRatio_{HSR}) + \beta_4 AE_{Time_{HSR}} + \varepsilon_{HSR} \quad (6-5)$$

$$U_{Air} = \beta_1 Cost_{Air} + \beta_2 Time_{Air} + \beta_3 \ln(FreqRatio_{Air}) + \beta_4 AE_{Time_{Air}} + \varepsilon_{Air} \quad (6-6)$$

- D_{ij} is the total high-speed passenger demand (HSR plus air transport demand) between cities i and j ;
- $S(Air|ij)$ is the mode share of non-stop air travel, or the probability of travellers choosing air transport over HSR for travel between cities i and j ;
- $D_{ij(Air)}$ is the total air passenger demand between cities i and j ;
- L_{ij} is the logsum term representing the consumer surplus of travelling (Ben-Akiva and Lerman, 1985);
- K is a multiplicative constant term;
- $P_i P_j$ is the product of the population in cities i and j , in millions;

- $I_i I_j$ is the product of the annual average income in cities i and j , in 1,000 U.S. dollars (2015);
- $SpecBoth_{ij}$ is a dummy variable that equals 1 if both cities i and j are special cities and 0 otherwise;
- $SpecNeither_{ij}$ is a dummy variable that equals 1 if neither city i nor j are special cities and 0 otherwise;
- β_{HSR} is the HSR alternative specific constant;
- $Cost_{HSR(or Air)}$: the travel cost of a given mode on a given journey, measured in U.S. dollars in 2015;
- $Time_{HSR(or Air)}$: the travel time of a given mode on a given journey, measured in hours;
- $FreqRatio_{HSR(or Air)}$: the ratio of each mode's frequency over the total service frequency, reflecting the importance (or the weight) of each mode on a given route.
- $AE_{Time_{HSR(or Air)}}$: the sum of access and egress (AE) time for HSR or air travel; access time is the drive time from origin city centre to origin rail station or airport, and egress time is the drive time from destination rail station or airport to destination city centre.

The parameters to be estimated are $K, \alpha, \beta, \delta, \vartheta, \psi, \beta_{HSR}, \beta_1, \beta_2, \beta_3, \beta_4$ in the above equations. As Jamin et al. (2004) stressed, directly including the departure frequency between city pairs would result in simultaneous equations, where a high service frequency results from the high travel demand; and at the same time the high-travel demand is partially caused by the high service frequency. To address this issue, this model replaces frequency by the ratio of each mode's frequency over the total service frequency. Essentially, now the frequency ratio variable only reflects the importance (or the weight) of each mode on a given route without directly equalling supply with demand (Doyme, personal communication). By using frequency ratio as

a variable, the null hypothesis of exogeneity cannot be rejected at 5% statistically significant level by the Hausman test, indicating that all regressors are exogenous. In addition, the gravity model (Eq.6-1) and the logit model (Eq.6-2) potentially have contemporaneous cross-equation correlations in their error terms, therefore, the Seemingly Unrelated Regression (SUR) method is adopted in the estimation. Coefficients in the logit model are determined by taking the logarithm of the ratios of air transport market share over HSR market share. Among the parameters to be estimated, 2α represents the population elasticity, 2β represents the income elasticity, and the value of time can be calculated from β_2/β_1 (Jamin, et al. 2004; Fridstrom and Thune-Larsen, 1989). To understand the variations in the effects of these influencing factors on travel demand over distance, I estimate the model first for all sample city pairs, and then for three distance groups separately: the short-distance routes (< 500 km), the medium-distance routes (500-1,000 km), and long-distance routes (> 1,000 km). The resulting parameter estimates are shown in Table 6-1 and will be discussed in detail in the next section.

6.3 Estimation Results and Discussion

All estimated parameters shown in Table 6-1 have the expected sign and order of magnitude. All coefficients in the full-sample estimation are highly statistically significant at the 0.1% level. The adjusted R^2 of both equations in the full-sample estimation and sub-distance estimations are all well above 0.8, indicating that the selected explanatory variables capture the majority of variance in the data and that the model predictions can fit the observed data well.

Table 6-1. Estimation results of high-speed transport demand model.

Variables	Coefficient	Full sample	Short-distance (< 500km)	Med-distance (500-1,000km)	Long-distance (>1,000km)
Multiplicative constant	K	9.1638*** (0.2678)	8.3213*** (0.6942)	10.2272*** (0.4039)	9.8108*** (0.4322)
Population	α	0.5558*** (0.0319)	0.7645*** (0.1497)	0.5399*** (0.0475)	0.4338*** (0.0438)
Income	β	0.8131*** (0.0622)	0.6211** (0.2096)	0.6846*** (0.0837)	0.8975*** (0.0937)
Special both	δ	0.3274*** (0.0464)	0.5759** (0.1706)	0.1737** (0.0571)	0.3850*** (0.0663)
Special neither	ϑ	-0.2447*** (0.0443)	-0.3113* (0.1529)	-0.1296* (0.0575)	-0.3202*** (0.0666)
Logsum	ψ	0.6378*** (0.0286)	0.3888*** (0.0636)	1.0120*** (0.1626)	1.0064*** (0.0794)
HSR alternative-specific constant	β_{HSR}	-0.3506** (0.1075)	0.9277* (0.5560)	-0.2214* (0.0994)	-0.5026*** (0.1510)
Travel cost	β_1	-0.0049*** (0.0010)	-0.0268** (0.0082)	-0.0057** (0.0021)	-0.0048*** (0.0012)
Travel time	β_2	-0.1859*** (0.0085)	-0.2808* (0.1076)	-0.2051*** (0.0168)	-0.2087*** (0.0110)
ln(Freq ratio)	β_3	0.4064*** (0.0164)	0.1855** (0.0680)	0.4045*** (0.0262)	0.2397*** (0.0250)
Access and egress driving time	β_4	-0.0048*** (0.0014)	-0.0158** (0.0047)	-0.0061** (0.0023)	-0.0037* (0.0017)
No. of observations		608	46	258	304
Eq.(1) Gravity Model R^2		0.8546	0.9179	0.8927	0.8559
Eq.(2) Logit Model R^2		0.8973	0.9617	0.9010	0.8298

(Note: *** Significant at the 0.001 level, ** Significant at the 0.01 level, * Significant at the 0.05 level; standard errors are shown in parentheses.)

This model is estimated based on the cross-sectional data in year 2015 at an aggregate level. Therefore, the model estimates provide short-run elasticities that shed light on some important characteristics of air and HSR travel in China in a relatively short term. Starting from the gravity model (Eq.6-1) estimates, the impact of population and income on travel demand is positive and statistically significant. This suggests that with all other factors being equal, city pairs with larger population sizes

or higher average income experience greater demand for high-speed travel. For the full sample, the estimated mean of the population elasticity is 1.12 (2×0.56). As expected, the influence of population on travel demand declines with travel distance; specifically, the estimated mean of population elasticity is 1.53 (2×0.765) on short-range routes, 1.08 (2×0.539) on medium-range routes, and 0.87 (2×0.434) on long-haul routes.

Income has a slightly larger impact on travel demand compared to population size. Under the full sample, the estimated mean of the income elasticity is 1.62 (2×0.81). Notably, this estimate is within IATA's (2007) review on the income elasticities, with a value between 1 and 2. In contrast to the population elasticities, the influence of income on travel demand increases with travel distance. Specifically, the income elasticity is lowest on short-haul routes at 1.24 (2×0.621) and increases to 1.37 (2×0.684) on medium-range routes and is the highest on long-haul routes at 1.79 (2×0.897). This can be explained by the fact that ticket prices of high-speed travel on short-distance routes are more affordable to passengers with lower income due to lower operating costs and higher competition from other substitutes such as tour bus. The increase in the income elasticity with distance range is also in line with IATA's (2008) previous findings for both developing and developed economies, which suggests that middle to lower income passengers are more likely to travel on short/medium haul routes, whereas people with higher income tend to travel more frequently over longer distances.

As expected, the parameter δ is positive, whereas ϑ is negative. The positive parameter δ means that for city pairs with both endpoint cities having special attributes (business centres or tourism hotspots), travel demand is typically higher. In

contrast, the negative ϑ suggests that if neither endpoint city has special attributes, they are less attractive to travellers with all other factors being equal.

Moving to parameters of the mode share model (Eq.6-2), it is found that the HSR alternative specific constants β_{HSR} in the HSR utility function (Eq.6-5) is negative and statistically significant in all cases except for short-range routes. This indicates that air transport is the preferred option except for travels below 500 km, everything else equal. In addition, the negative HSR alternative specific constant increases in magnitude from medium distance to long distance, suggesting that air transport becomes increasingly preferable as travel distance gets longer. Furthermore, both travel cost and travel time have negative coefficients with high statistical significance, which reflect the general desire for fast and low-cost travel.

The value of time (VOT), i.e., β_2/β_1 for the full sample estimation is \$37.93 (-0.1859/-0.0049), which suggests that when choosing between air transport and HSR, travellers in China are willing to pay \$38 more per one-hour reduction in travel time on average. Notably, this estimate of the VOT is close to the value of \$48.88 recommended by the US Department of Transportation for inter-city air and HSR travel and used by the California HSR analysis (PB, 2014). The slightly lower value of the Chinese VOT can be explained by the lower income levels compared to the U.S. The estimated VOT for short-distance travel is \$10.48 (-0.2808/-0.0268), \$35.98 (-0.2051/-0.0057) for medium-distance travel, and \$43.47 (-0.2087/-0.0048) for long-distance travel.

All coefficients of the frequency ratio are positive and highly statistically significant, which suggests that passengers tend to choose the transport mode operating with higher frequency, everything else equal. Lastly, as expected, the access and egress time between city centre and local rail station or airport has negative and

statistically significant effect on the mode share, implying that passengers prefer the transport mode with better accessibility from/to city centre, all other factors equal.

The model presented in this section could be used to project the demand for air travel specifically under the competition of HSR into the future. The next section presents air travel demand projections using the 2015 and the future planned 2025 HSR network, between 2015 and 2050.

6.4 Future Aviation Demand under HSR Competition

This section firstly presents the O-D demand projections for Chinese domestic air travel under the 2015 and the future planned 2025 HSR network, using the demand model discussed in the previous section. Based on the projected aviation demands, the additional aviation capacity required to meet the growing demands under different scenarios is estimated. Specifically, it is expected that without further expansion of the 2015 HSR network that will lead to more passengers diverted from air transport to HSR, air transport system would need larger capacity expansions compared to aviation system under the future planned 2025 HSR network.

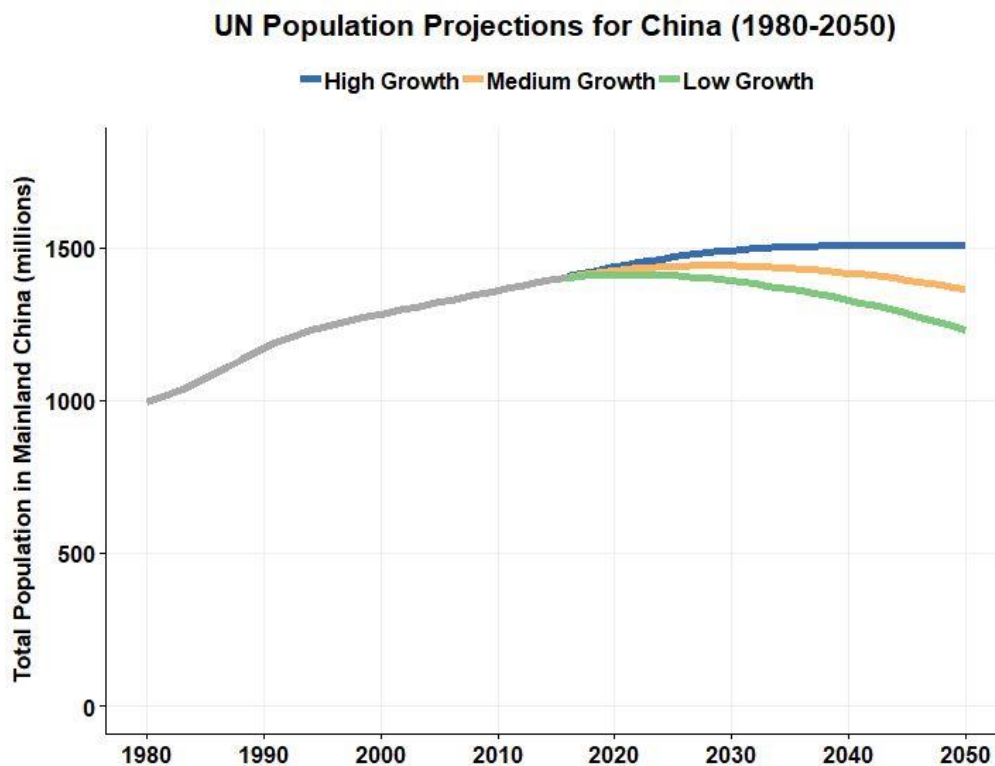
6.4.1 Future Aviation Demand under the 2015 and the 2025 HSR

Network

In order to predict aviation demand into the future, projections for population, income, and jet fuel prices are required (Eq. 6-1 to Eq. 6-6). Projections on China's future urban population is obtained from the UN World Population Prospects 2017 (United Nations, 2017); average GDP per capita is derived from the reference-case long-term GDP projections made by the OECD Economic Outlook (2018) for China

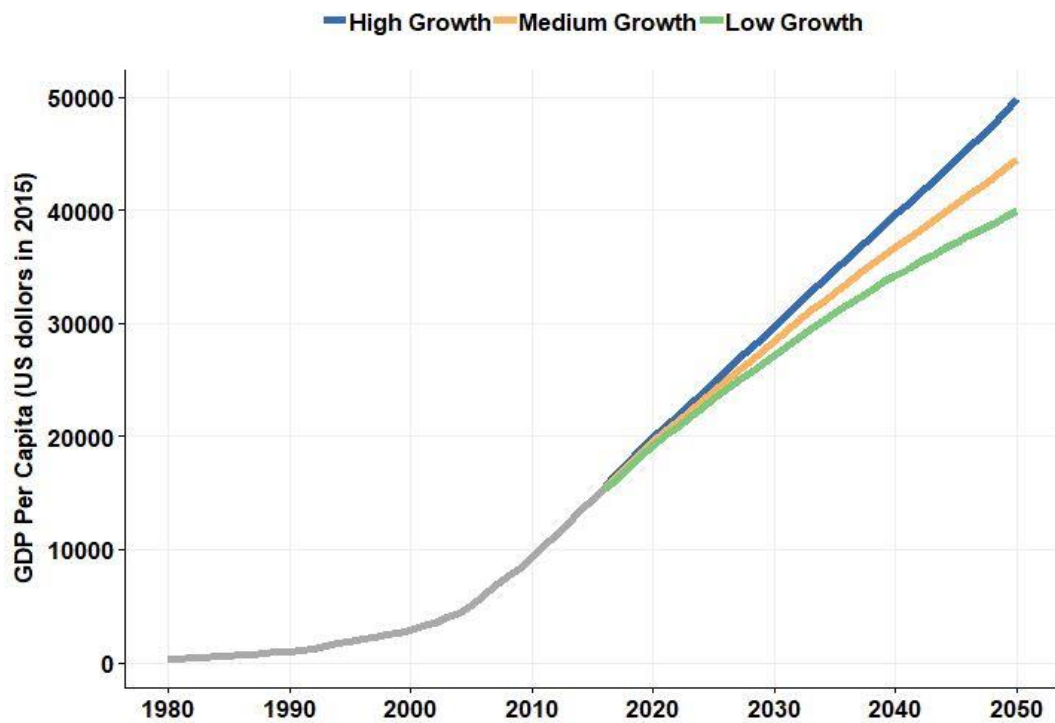
(the high and low GDP growth are derived by +/- 1% per year of the annual GDP growth in the reference case). Furthermore, projections for Jet-A fuel price in the U.S. are obtained from the EIA annual energy outlook (2019) and are used directly for my projections, given that jet fuel prices do not vary significantly by world region. Three distinct future scenarios with respect to population growth, GDP per capita growth, and jet fuel prices are simulated and compared.

- 1) High Growth Future: high growth in population and GDP per capita, and low growth in jet fuel prices;
- 2) Central Growth Future: medium growth in population, GDP per capita, and jet fuel prices;
- 3) Low Growth Future: low growth in population and GDP per capita, and high growth in jet fuel prices.



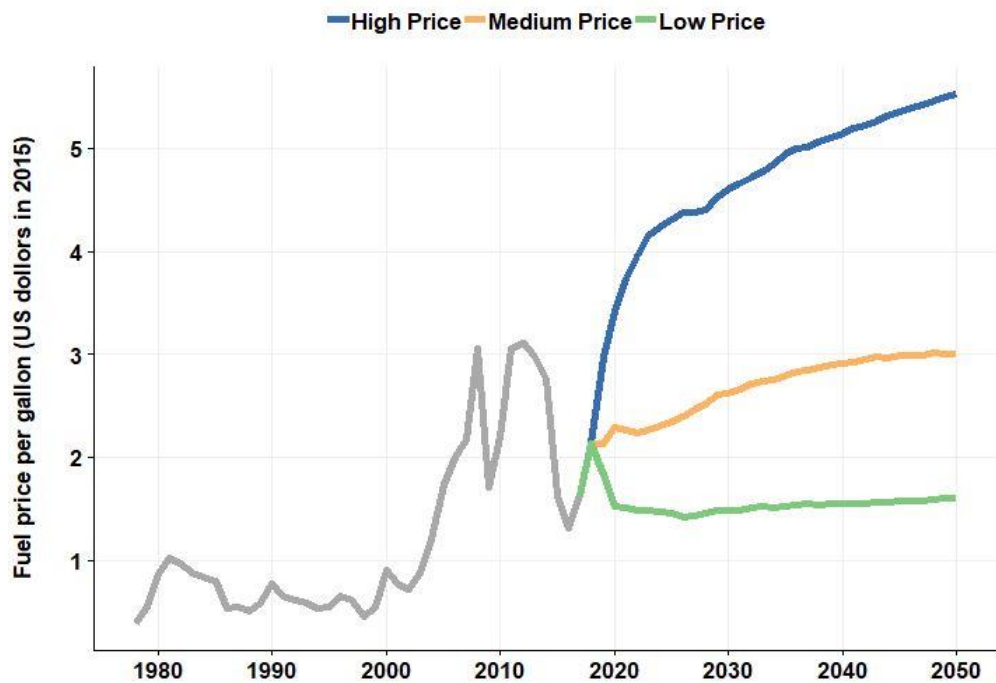
(a)

GDP Per Capita Projections for China (1980-2050)



(b)

Jet-A Fuel Price Projection by EIA (1978-2050)



(c)

Figure 6-3. Development of population (a), GDP per capita (b) and fuel price (c) in China, history (1980-2015) and projections (2016-2050).

Figure 6-3 shows the historical development (1980-2015) and the future projections (2016-2050) of three scenarios on population (a), GDP per capita (b), and fuel prices (c) used in this study. The historical data on China's annual population and GDP are obtained from the Chinese Statistical Yearbook (2016). Data on historical jet fuel prices in the U.S. are obtained from the EIA annual energy outlook (2019).

Apart from city populations, income, and fuel prices, additional input variables are also required. In the gravity model (Eq. 6-1), for simplicity, I assume that special attributes of Chinese cities remain unchanged during the projection period. In the utility function of air transport (Eq. 6-6), journey time by air transport and travel time between city centre to airport are also assumed unchanged. In addition, future increases in flight frequency are assumed to follow the GDP growth of O-D city pairs; and prices for air travel are predicted by the airfare model developed in Chapter 4, which takes projections on fuel prices as a key input variable (Wang, et al., 2018).

With respect to the HSR input variables in Eq. 6-5, projections for future HSR fares, journey time, and service frequency require two steps. Firstly, given that new O-D city pairs are planned to be connected by the 2025 HSR network, HSR fares, journey time, and service frequency on these routes are currently unknown. Therefore, the initial values of these variables on the new routes must be estimated using the 2015 data. After that, possible increase of future HSR fares and frequency of all O-D city pairs under the 2015 and 2025 HSR network need to be projected, respectively.

Similar to air travel, journey time of HSR travel is assumed unchanged on the existing O-D pairs; journey time of new O-D pairs under the 2025 HSR network is derived from HSR distance and average HSR speed and remains constant since 2025. Access and egress time on the existing routes are also assumed unchanged, whilst travel time between city centre to the planned new HSR stations is the average

access/egress driving time from existing sample cities. Regarding HSR frequency, a simple linear regression is estimated where HSR frequency is determined by HSR distance, O-D population, and income (Table 6-2: Regression 1). Using this regression model, both the initial HSR frequency on the new HSR-connected routes under the 2025 HSR network and the projections of future HSR frequency could be estimated under the high-, central-, and low-growth scenarios.

Table 6-2. Regression results used to estimate HSR fares and frequency on new HSR routes introduced in the 2025 network.

Dependent variable	Independent variables	Coefficients	Std. Error	t-value
<i>Regression 1:</i>				
$\ln (Freq)_{HSR}$	Constant	16.173***	0.564	28.670
	$\ln (HSR\ Distance)_{od}$	-1.737***	0.063	-27.335
	$\ln (Population)_{od}$	0.567***	0.456	12.409
	$\ln (Income)_{od}$	0.365***	0.106	3.425
No. of Obs.	608	Adjusted R^2	0.637	
<i>Regression 2:</i>				
$\ln (Fare)_{HSR}$	Constant	-0.291***	0.173	-7.163
	$\ln (HSR\ Distance)_{od}$	0.876***	0.030	29.152
	$\ln (HSR\ operating\ cost)_{od}$	0.167***	0.012	15.405
	$\ln (HSR\ freq\ share)_{od}$	-0.110***	0.021	-5.318
No. of Obs.	608	Adjusted R^2	0.791	

(Note: ***Significant at the 0.001 level, **Significant at the 0.01 level, *Significant at the 0.05 level.)

Finally, with respect to HSR fares, according to World Bank (2019), HSR prices in China were unchanged from 2007 to 2016, apart from a 5 percent reduction in 2011 due to the massive HSR accident happened in that year. This is because, as Li et al. (2019) stressed, China's railway sector remains state owned and highly regulated;

thus, HSR pricing decisions have been tightly controlled by the central government in order to maximize social welfare. As a result, assuming constant HSR prices based on the observed 2015 HSR fares seems plausible for the demand projection. However, given that in 2016, the central government decided to delegate the pricing power of HSR to CRC (State Council, 2016), it is possible that HSR prices could become relatively more flexible in the future for cost recovery purpose.

Based on this assumption, a linear regression model is estimated for HSR prices, where HSR fares are regressed by HSR travel distance, HSR frequency, and train operating costs (Table 6-2, Regression 2), using the 2015 data. World Bank (2019, Table 6.1) estimated that the unit cost of China's HSR train operating cost is CNY 0.19 per pkm for the D type trains (with speed of 200-250 kph) and CNY 0.23 per pkm for the G type trains (with speed of 300-350 kph). Using these unit cost values and the observed annual PKM, total operating costs of each HSR-connected city pair are calculated. As can be seen in Regression 2 (Table 6-2), coefficients of all the three independent variables are statistically significant at 1% level and with expected signs, and the adjusted R^2 is 0.79, suggesting that the model fits the observed HSR fares well.

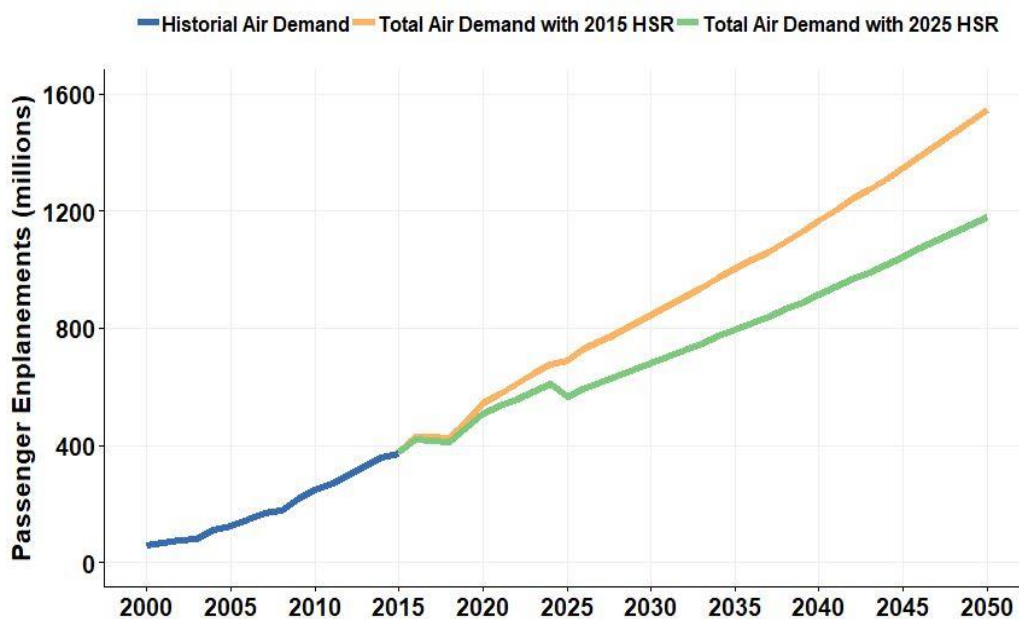
Using the regression model, both the initial HSR fares of the new O-D pairs under the 2025 HSR network and future HSR fares of all O-D pairs could be estimated. For the new O-D pairs, HSR frequency is estimated by Regression 1 (Table 6-2) and used to derive HSR frequency share against the flight frequency on this route; annual train operating costs are calculated by multiplying estimated annual PKM⁷ by the corresponding unit cost (¥ 0.19/pkm for 200-250 kph trains or ¥ 0.23/pkm for 300-350 kph trains). For future projections of HSR fares, it is assumed that the unit costs of

⁷ Annual PKM = (seats per train × average utilisation rate × HSR distance) × annual HSR frequency

HSR operation would increase at the same rates of GDP growth, and as described previously, future HSR frequency are also partially determined by population and income (Table 6-2: Regression 1); as a result, future HSR fares could increase differently under the high-, central-, and low-growth scenarios.

Based on the inputs described above, the demand for air transport under the 2015 and the planned 2025 HSR network is projected and compared for the period 2015 to 2050. Figure 6-4 shows projections for the domestic Chinese air transport demand under the 2015 HSR network and the future planned 2025 HSR network. The domestic historical enplanements are obtained from the China Statistical Yearbook (2016). Notably, although city pairs that will be connected by new HSR segments are available from the official HSR network plan, the first year of operation remains unknown. As a result, it is assumed that all the planned new HSR routes will start service in 2025, except for a few post-2015 segments that are already in operation while this study has been conducted.

**Projections for Domestic Chinese Air Passenger Demand (2015-2050)
(High Growth Scenario)**



(a)

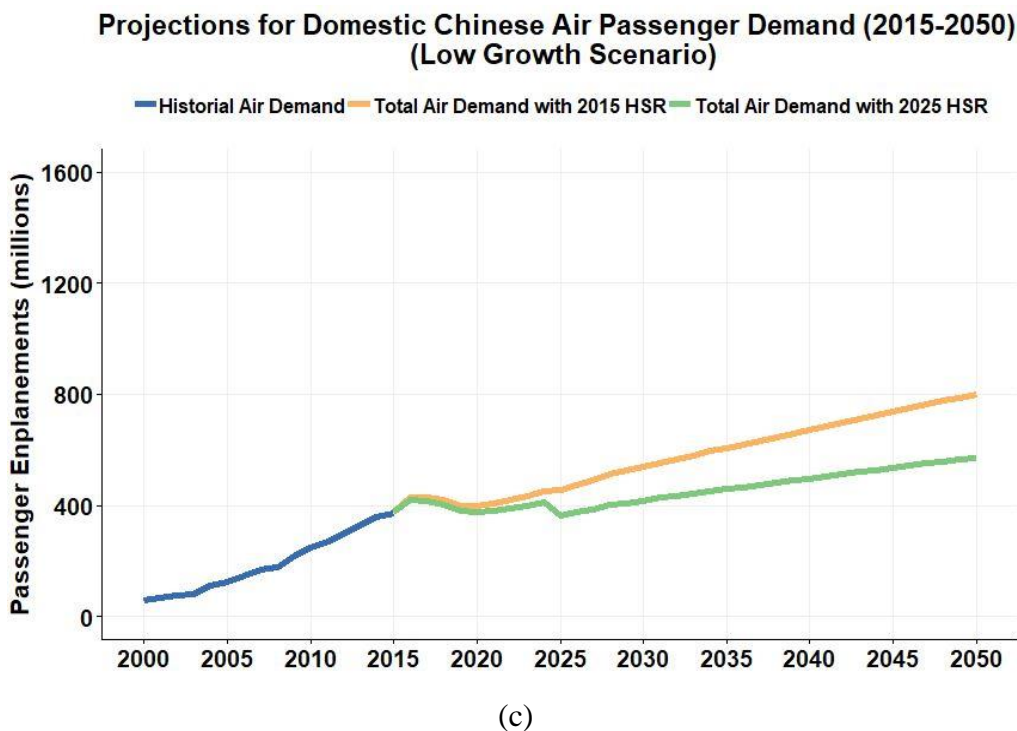
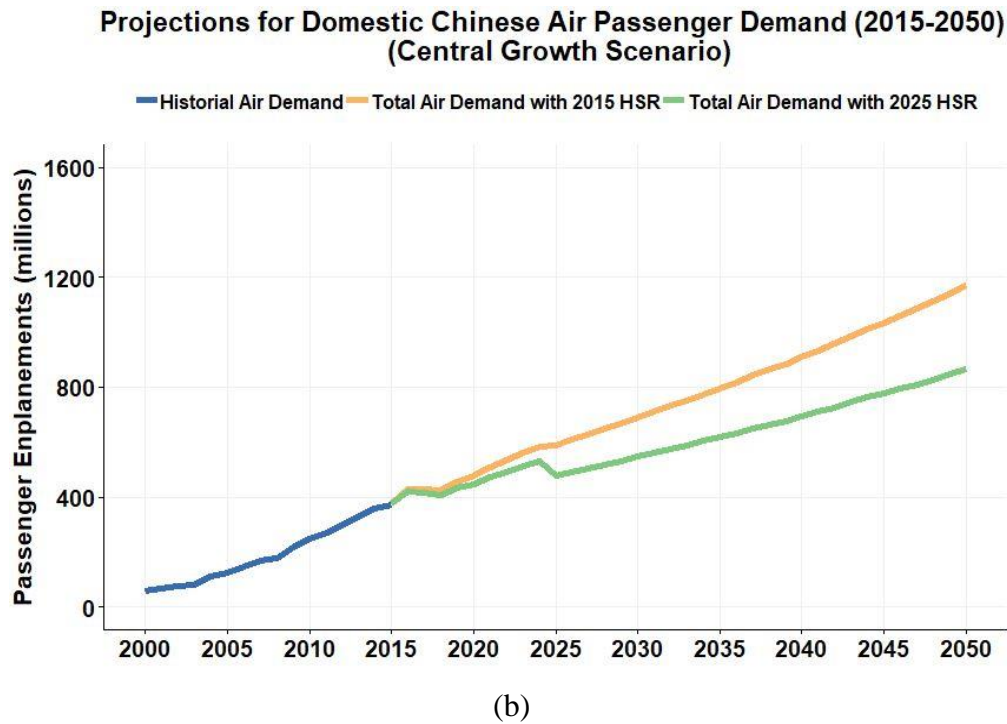


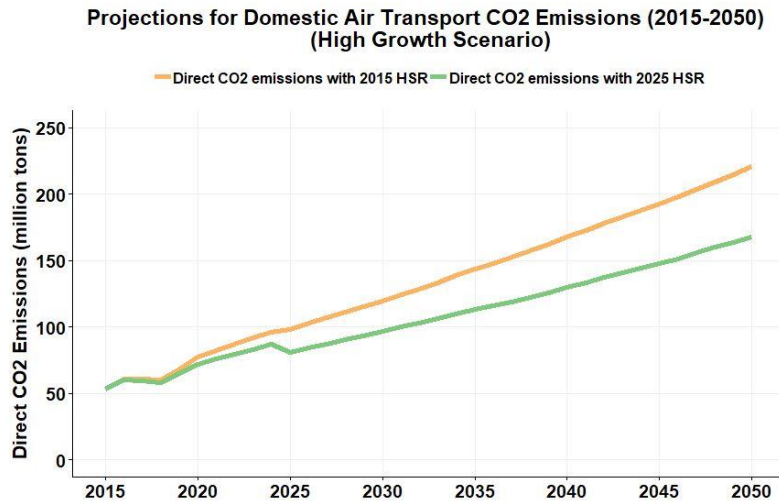
Figure 6-4. Historical (2000-2015) and projections of domestic air travel demand under the 2015 and the planned 2025 HSR network in China (2016-2050).

As can be seen in Figure 6-4, for each growth scenario, annual aviation demand is projected to be smaller under the enhanced 2025 network than the demand under the existing HSR network. Therefore, as a result of HSR substitution, more air travel

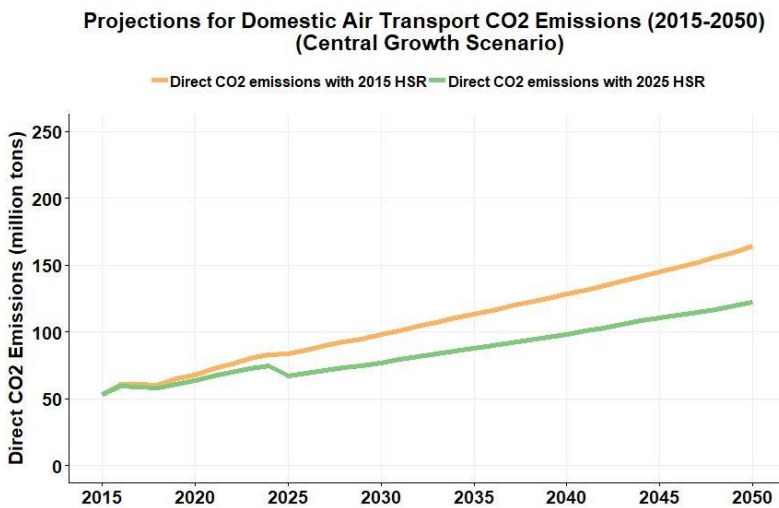
passengers are predicted to shift to HSR, after the current HSR network is expanded. Notably, in Figure 6-4, the decreasing demand during 2016-2018 is due to high fuel prices (Figure 6-3c). The small deviations of the aviation demand between the two HSR networks before 2025 are the additional diverted demand to HSR travel, resulting from the observed post-2015 new HSR routes that started operation during the period 2016 to 2019 (when this study is conducted). In 2025, the drop of aviation demand under the 2025 HSR network across all projections are a result of the assumption mentioned earlier that all the new HSR segments will start operation in 2025.

As shown in Figure 6-4, future air transport demand is expected to increase the most under the “High Growth” scenario and the least under the “Low Growth” scenario. Specifically, in the high-growth future (Figure 6-4a), annual air passenger demand under the 2015 HSR network could increase from 370 million passengers in 2015 to 1,544 million in 2050, a 317% growth. In comparison, annual demand under the 2025 HSR network could grow by 219%, reaching to 1,180 million passengers in 2050. In contrast, annual air transport demand in the low-growth scenario (Figure 6-4c) would see a more modest 117% increase from 370 million passengers in 2015 to 802 million in 2050 under the 2015 HSR network, and a 55% increase to 573 million passengers in 2050 under the 2025 HSR network.

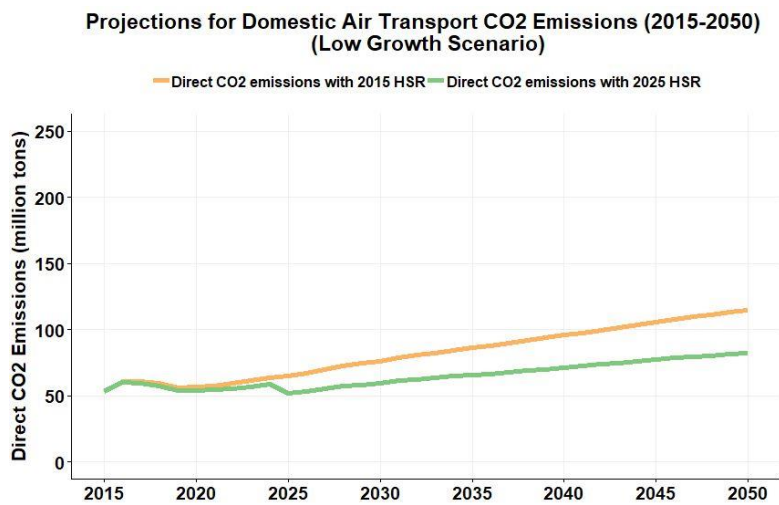
Figure 6-5 depicts projections for the annual direct CO₂ emissions associated with the projected domestic aviation demand under the 2015 and 2025 HSR network, in the high-growth (a), the central-growth (b), and the low-growth (c) scenario, respectively. Assuming a 2% per year improvements in aircraft fuel efficiency (Schäfer et al., 2016), fuel use and CO₂ emissions by O-D airport pair are derived from the PIANO-X aircraft performance model (Lissys Ltd, 2017), based on the projected demand.



(a)



(b)



(c)

Figure 6-5. Direct aviation CO₂ emissions under the 2015 and the planned 2025 HSR network, assuming a 2% per year improvements in aircraft fuel efficiency.

As shown in Figure 6-5, due to the expanded HSR network, total direct CO₂ emissions from domestic aviation could be significantly lower under the 2025 HSR network, as more passengers are expected to shift from air travel to HSR in the future. With the assumed 2% per year improvements in aircraft fuel efficiency, in the high-growth scenario (Figure 6-5a), annual aviation CO₂ emissions could increase by 309% from 54 MtCO₂ in 2015 to about 221 MtCO₂ in 2050 under the 2015 network, compared to a 209% increase under the 2025 network to 167 MtCO₂. In comparison, emissions in the low-growth case (Figure 6-5c) would have a modest growth by 113%, reaching 115 MtCO₂ in 2050 under the 2015 network and by 52% to 82 MtCO₂ under the 2025 network, respectively.

6.4.2 Matching Capacity to Air Traffic Demand

In order to meet the projected increase in aviation demand under the 2015 and the future planned 2025 HSR network (Figure 6-4), the aviation system may require additional capacity compared to its current capacity. This section estimates the need for capacity expansions in the aviation system to meet the growing demands. Estimates of capacity expansions should follow the principle that existing capacity must be fully utilized before any infrastructure expansion (OECD/ITF, 2014). Thus, the year that a given airport reaches its current capacity is firstly estimated.

In this study, I define airport capacity as the maximum number of air traffic movements (ATMs, i.e. arrivals and departures) that can be accommodated at an airport for an hour, which is also known as the declared hourly capacity of an airport. The declared capacity of all Chinese airports are obtained from the National Report on Civil Aviation Operational Efficiency by CAAC (2015). To evaluate the point in time at which these airports will reach their maximum capacity, flights for all non-

HSR involved segments (including both domestic and international) departing from or arriving at Chinese airports is projected using the AIM2015 model (Dray et al, 2019), using consistent input assumptions. Together with the projected flights on the routes with HSR competition from the demand model developed in this study, the annual total ATMs (including both domestic and international flights) between 2015 and 2050 at all the Chinese airports are obtained.

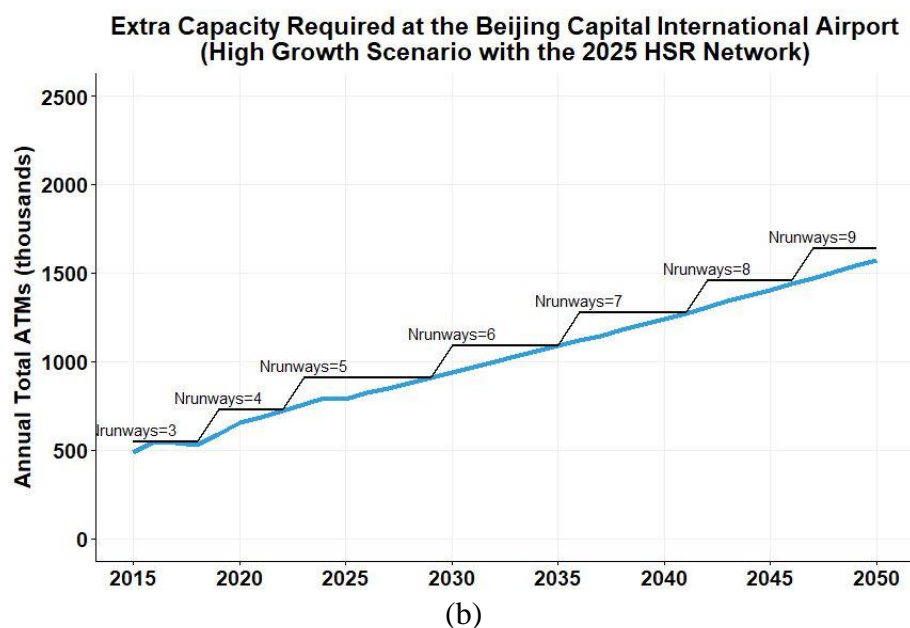
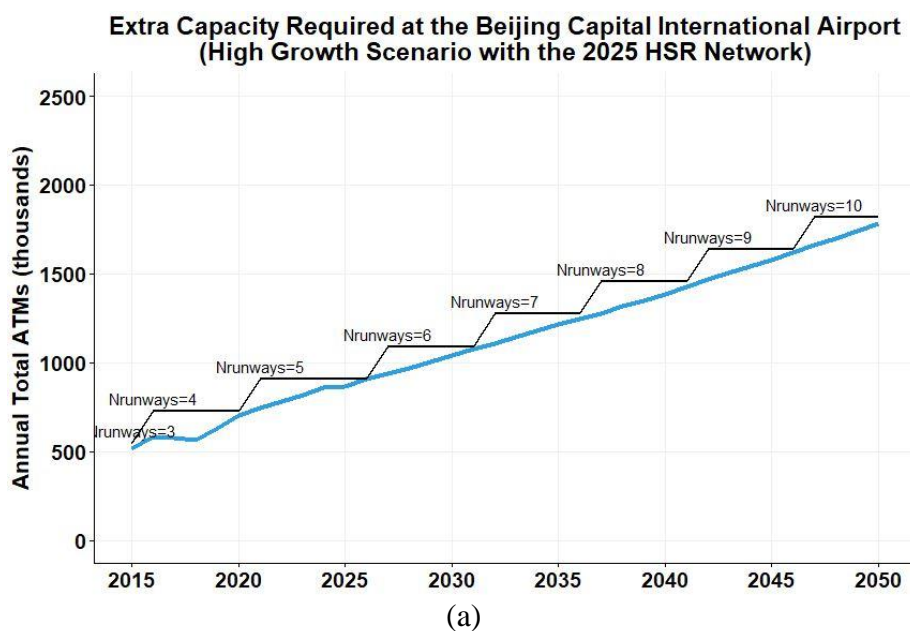


Figure 6-6. Number of runways needed at the PEK airport under the High Growth Scenario.

Through comparing each airport's annual ATMs against its annual capacity, assuming 17 hours daily operation for 365 days a year, the year at which the current capacity is exceeded is estimated. Notably, airports could also match their capacity with demand via longer daily operational hours or advanced operational procedures (Janic, 2004), however this study does not consider these strategic and tactical measures in the evaluation.

Once an airport has reached its capacity, it is assumed that one additional runway (with the same configuration of the existing runway(s) of this airport) is added at a time, until the expanded capacity is about to be exceeded again. Based on this mechanism, the total number of extra runways that would be needed to meet the projected demand between 2015 and 2050 is estimated for all the Chinese airports. Figure 6-6 shows the number of runways the Beijing Capital International Airport would need to meet its projected annual ATMs between 2015 and 2050.

With effectively only one major airport that is already close to its full capacity, i.e. the Beijing Capital International Airport (PEK) (3 runways with a declared capacity of 88 ATMs/hour), Beijing would need 7 additional runways by 2050 under the high growth scenario, unless the 2015 HSR network is expanded (a). In contrast, under the future planned 2025 HSR network (b), only six additional runways would be needed. Meanwhile, the years at which new capacity would need to be introduced are also slightly postponed under the 2025 network compared to the 2015 network. Notably, this estimation of future required aviation capacity in Beijing is very close to reality, i.e. the new Beijing Daxing International Airport is designed to have seven runways and is expected to absorb the capacity pressure on the PEK airport (NDRC, 2014). Using this approach, additional capacity that would be required to meet the projected aviation demand for every Chinese airport covered in study is estimated.

6.5 Lifecycle CO₂ Emissions Assessment

Having projected future aviation demand and the possible additional capacity required in the Chinese aviation system to meet this demand under the 2015 and the future planned 2025 HSR network, respectively, this section starts to assess the lifecycle CO₂ emissions of both transport modes. It firstly assesses the cumulative lifecycle CO₂ emissions from 2016 to 2050 for the two high-speed transport systems based on the projected total aviation and HSR demand. Following that, it estimates the possible net emissions savings from HSR substitution using the marginal diversion of aviation demand from the existing 2015 network to the expanded HSR network.

6.5.1 HSR and Air Transport Lifecycle Emissions

According to Chester (2008), energy use and emission estimates for passenger transportation modes typically overlook the non-operational components, including vehicle manufacturing and maintenance, infrastructure construction, and fuel production. However, emissions from these components might account for significant proportion of a transport mode's lifecycle emissions. Thus, assessing CO₂ emissions of both air transport and HSR from a lifecycle perspective could provide a more comprehensive understanding to their environmental impacts.

6.5.1.1 HSR Lifecycle Emissions

As discussed in Chapter 2, lifecycle emissions of a transportation mode consists of emissions from both operational and non-operational phases. Chester (2008) estimated the lifecycle CO₂ emissions for the proposed California HSR (CAHSR) system, with approximately 700 miles (1,127 km) of track and 25 stations connecting

San Diego, Los Angeles, San Francisco, and Sacramento. Technical parameters of the proposed the CAHSR such as vehicle weights, seats, and electricity intensity are provided by CAHSR Authority (2005). Given that key input values of the Chinese HSR are unavailable, in order to apply Chester's HSR inventory input to the Chinese HSR, some key technical parameters with respect to major vehicle models of the CHSR and the CAHSR are summarised and compared in Table 6-3.

Table 6-3. Technological specification of main CHSR vehicles and the proposed CAHSR vehicle by Zhou (2014) and Chester (2008).

HSR Model	Type	Electricity Intensity (kWh/seat-km)	Weights (tonnes)	Cars	Seats	Length (metres)	Max Speed (km/h)
CRHA Series	D1	0.037	420.4	8	660	213.5	250
CRHB Series	D2	0.058	690.0	16	1,230	426.3	250
CRH380L Series	G1	0.058	890.0	16	1,061	399.3	350
CRH380 Series	G2	0.037	399.4	8	556	215.3	380
CAHSR	N/A	0.363	730.0	16	1,200	450.6	350

As shown in Table 6-3, there are mainly four series of HSR trains currently in service in China. The 'D' type vehicles operate at lower maximum speed compared to the 'G' type vehicles. Both types come with either 8 or 16 carriages. In contrast, the California HSR is projected to use a large-size train (16 cars with 75 seats each).

Chester (2008) adopts an electricity intensity at 0.363 kWh/seat-km for the proposed CAHSR. Although this value is provided by the CAHSR Authority (2005), according to Chester and Horvath (2012), this electricity intensity is significantly over-estimated. Because the electricity intensity of the Chinese HSR trains are unavailable, this study uses electricity intensity values of the prototype CHSR vehicles: 0.037 kWh/seat-km for the 8-carriages HSR vehicles and 0.058 kWh/seat-km for the 16-carriages HSR vehicles.

Table 6-4. Emission factors of HSR lifecycle CO₂ emissions components based on Chester (2008).

Category	HCR LCI Component	Chester's calculation based on	Chester's Emission Factors		Emission Factors in This Study
Vehicle Operation	Propulsion	Electricity intensity of a 1,200-seats CAHSR train: 271 kWh/VMT, equivalent to 0.363 kWh/seat-km	87	gCO ₂ /PMT	Small train: 35 gCO ₂ /PKT Large train: 54 gCO ₂ /PKT
	Idling		2.2	gCO ₂ /PMT	Small train: 0.5 gCO ₂ /PKT Large train: 0.9 gCO ₂ /PKT
	Auxiliaries		4.7	gCO ₂ /PMT	Small train: 1.2 gCO ₂ /PKT Large train: 1.8 gCO ₂ /PKT
Vehicle Manufacture	Train Manufacture	Weight per train: 730t	2,127	tCO ₂ /train	2.9 tCO ₂ /ton of train
Vehicle Maintenance	Routine Maintenance	Weight per train: 730t	1,329	tCO ₂ /train	1.8 tCO ₂ /ton of train
	Flooring	Vehicle dimensions	140	tCO ₂ /train-life	4.7 tCO ₂ /train-year
	Cleaning	Vehicle dimensions	8.5	tCO ₂ /train-life	0.3 tCO ₂ /train-year
Infrastructure Construction	2 platforms (720×15×2 ft, or 220×4.6×0.6 m per station)	Concrete per station: 43,000 ft ³ (1,217 m ³)	Concrete production: 609 kgCO ₂ /yd ³ (798 kgCO ₂ /m ³)		4,060 tCO ₂ /platform
		Subbase per station: 22,000 ft ³ (623 m ³)	Subbase materials: 35 kgCO ₂ /yd ³ (46 kgCO ₂ /m ³)		119 tCO ₂ /platform
		Steel per station: 32,000 lbs (14.5 t)	Steel production 543 kgCO ₂ /yd ³ (711 kgCO ₂ /m ³)		4 kgCO ₂ /platform

Category	HCR LCI Component	Chester's calculation based on	Chester's Emission Factors	Emission Factors in This Study
	Track Construction*: 700 miles (1,127 km) track length in total	Concrete: 4.86×10 ⁵ ft ³ per mile (8.57×10 ³ m ³ per km)	Concrete production: 609 kgCO ₂ /yd ³ (798 kgCO ₂ /m ³)	3,927 tCO ₂ /km-track
		Subbase materials: 2.86×10 ⁵ ft ³ per mile (4.97×10 ³ m ³ per km)	Subbase materials: 35 kgCO ₂ /yd ³ (46 kgCO ₂ /m ³)	133 tCO ₂ /km-track
		Steel: 3.71×10 ⁵ lbs per mile (1.04×10 ² t per km)	Steel production 543 kgCO ₂ /yd ³ (711 kgCO ₂ /m ³)	5.5 tCO ₂ / km-track
		Power structures: \$4.86×10 ⁴ per mile (\$3.02 ×10 ⁴ per km)	728 tCO ₂ /\$million	22 tCO ₂ /km-track
Infrastructure Maintenance	Station, Track Maintenance	5% of the station/track construction emissions.		
Infrastructure Operation	Lighting	0.45M kWh/platform-year		China's carbon intensity for power generation: 2015 level versus IEA projections
	Escalators	2 escalators, 4.7 kW/h, 15 hours/day, 365 days	California carbon intensity for power generation:	
	Train control	4.7×10 ⁴ kWh/year per mile of track	260 gCO ₂ /kWh	
	Miscellaneous	8 ×10 ⁴ kWh/platform-year		
Electricity production	Power T&D losses	Power T&D loss rate	California T&D loss rate: 8.7%	China T&D loss rate in 2015: 5.1%

(Note: * tunnel and bridge construction are not included.)

With these technological parameters, a bottom-up approach is adopted to estimate the CHSR lifecycle emissions based on the CAHSR's lifecycle emissions factors from all lifecycle components. Table 6-4 provides emissions factors by Chester (2008) and converted to estimate the CHSR lifecycle CO₂ emissions.

HSR Operational Emissions

As shown in Table 6-4, emissions from the operational phase of HSR are a result of producing the electricity consumed by active train operation (propulsion) and inactive operation (idling and auxiliaries) (Chester, 2008). The operational emissions of HSR are determined by the electricity intensity of HSR vehicles. Based on the employed electricity intensities of the CHSR (see Table 6-3), the emission factor per PKT (Table 6-4) is estimated, using information on seats per train, average occupancy rate of China's HSR in 2015, and the carbon intensity of power generation in China (IEA, 2018). The total operational phase CO₂ emissions of the CHSR can be then computed based on Eq. (6-7):

$$OperationalCO_{2HSR} = \sum_c \{ (gCO_2/PKT)_{OP} \times (HSR.Pax_{ij} \times HSR.Dist_{ij}) \}, \quad i \neq j \quad (6-7)$$

In addition, given that HSR operational CO₂ emissions are generated from electricity consumption, which is determined by the carbon intensity of electricity generation, it is also important to account for the decarbonization of China's power generation sector. In order to compare the impact of carbon intensity in electricity generation to the HSR lifecycle CO₂ emissions, this study computes the HSR lifecycle emissions under two carbon intensity scenarios: one with a fixed carbon intensity of 2015 at 657 gCO₂/kWh (IEA, 2018) over the period 2016 to 2050, which aims to assess the HSR lifecycle CO₂ emissions if China stops decarbonizing its power sector; and the other scenario computes the HSR lifecycle emissions with the IEA (2019)

projected carbon intensity of China's power sector between 2016 and 2040, as shown in Figure 6-7.

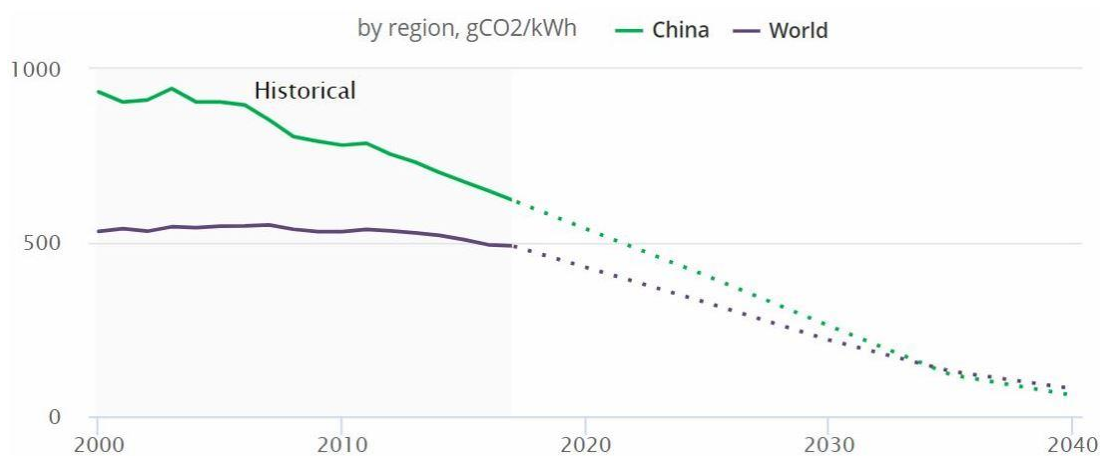


Figure 6-7. Historical (2000-2015) and projected (2016-2040) carbon intensity of electricity generation in China, IEA (2019).

According to the IEA, China's CO₂ intensity of power generation is expected to decline significantly from the level of 2015, and in 2040, China would achieve a low carbon intensity at 61 gCO₂/kWh given its massive development of renewable and nuclear energy. After 2040, it is assumed that China will achieve a zero-carbon electricity generation in 2050 and the yearly carbon intensities between 2040 and 2050 are then interpolated.

HSR Non-operational Emissions

As shown in Table 6-4, the HSR non-operational phases include vehicle components (manufacturing and maintenance), infrastructure components (construction, operation, and maintenance), and electricity production. To calculate the non-operational HSR CO₂ emissions, a bottom-up approach is adopted to estimate the CHSR lifecycle CO₂ emissions from those of the California HSR values. The detailed estimation approach is described below for each component.

1) HSR Train Manufacturing

Train manufacturing emissions are prorated based on train weights. As shown in Table 6-4, a total of 2,127 tCO₂ are generated from manufacturing a CAHSR train with a weight of 730 tonnes. This is equivalent to 2.9 tCO₂ per tonne of an HSR train manufactured. This value is then applied to the CHSR train weights (Table 6-3) and converted using China's carbon intensity for electricity generation. Having calculated the manufacturing emissions per train, the number of new trains required each year is estimated. Firstly, the total number of HSR trains required on a given O-D city pair is estimated based on daily operational frequency and journey time, assuming a 16 hours' daily operation. Driven by the increase in annual HSR frequency, the number of additional trains required on this route is estimated by comparing the number of trains required this year and in the previous year. It is assumed that new trains are manufactured in the year before their operation, thus the emissions factor of the previous year is applied for estimating manufacturing emissions.

2) Train Maintenance

Similar to HSR train manufacturing, emissions for train routine maintenance are also prorated based on train weights. The same conversion approach is adopted: annual emissions from train maintenance are calculated and applied to the period 2015-2050 (Table 6-4). Emissions from vehicle cleaning are estimated based on the electricity consumption per vacuuming operation and train dimensions. Emissions from flooring maintenance are determined from carpet and floor covering material production based on the flooring replacement costs and train dimensions (Chester, 2008). Since dimensions of the CHSR trains are not available, flooring and cleaning emissions of the CAHSR are directly applied to the CHSR trains, except for the use of China's electricity intensity for power generation.

3) Infrastructure Construction

Infrastructure construction includes both construction for rail stations and high-speed rail tracks. According to Chester (2008), each of the 25 stations of the CAHSR has 2 platforms with the dimensions 720 ft long by 15 ft wide by 2 ft high (220 m long by 4.6 m wide by 0.6 m high). Constructing a 2-platforms station requires materials of 43,000 ft³ (1,217 m³) concrete, 22,000 ft³ (623 m³) subbase material, and 32,000 lbs (14.5 t) steel (Chester, 2008). Therefore, material requirements for concrete, subbase material, and steel for constructing 1 m³ of the platform is calculated first. Next, emissions factors for producing these materials (Table 6-4) are used to calculate total CO₂ emissions from material production in constructing a typical Chinese HSR platform. The dimension of a typical Chinese HSR station platform is 450 m long, 12 m wide, and 1.3 m high (Gaotie.cn, 2018).

Having estimated emissions generated per platform, emissions from constructing new HSR stations are estimated. Importantly, under the existing 2015 HSR network, emissions from infrastructure construction are zero because the infrastructure is already in place. In contrast, for the future planned 2025 HSR network, there are 17 new HSR stations to be constructed in the sample cities by 2025. Because the number of platforms of each station is not known, for the future stations, it is scaled based on the number of platforms per million city population from the existing 41 HSR stations. For track construction, a similar approach is adopted to estimate emissions generated from producing materials for constructing 1 kilometre of HSR track. Following that, total CO₂ emissions from constructing the expanded track length are calculated for the 2025 HSR network.

4) Infrastructure Operation

Infrastructure operation mainly involves operations at rail stations, including station lighting, escalator usage, train control, and miscellaneous. As shown in Table 6-4, for station lighting, escalators, and miscellaneous, electricity consumption of each item per platform is firstly calculated and then applied to the number of platforms of each HSR stations. Emissions from station operations under the 2015 HSR network covers only the existing 41 HSR stations, whereas the 2025 HSR network calculates station operational emissions for both the existing stations and the new stations starting operation in 2025. For train control, given that it is based on electricity consumption per mile of track per year (Table 6-4), this parameter is applied to the total HSR track length under the 2015 and the 2025 HSR network, respectively, and compute the emissions with corresponding carbon intensity of power generation.

5) Infrastructure Maintenance

Emissions from station and track maintenance are assumed to be 5% of the station/track construction emissions (Chester, 2008, Table 63). Notably, for the 2015 HSR network, infrastructure maintenance covers only the existing HSR stations and tracks, whereas for the 2025 HSR network, both existing and new stations and tracks are included for estimating the maintenance emissions.

6) Electricity Distribution Losses

Emissions from electricity losses from power transmission and distribution (T&D) should also be included in the HSR lifecycle emissions. Firstly, annual electricity consumption from all HSR components are calculated. The produced electricity and the amount of electricity losses from T&D are derived based on China's power T&D loss rate. For simplicity, a constant power T&D loss rate of 2015 at 5.10% (IEA, 2019) is applied.

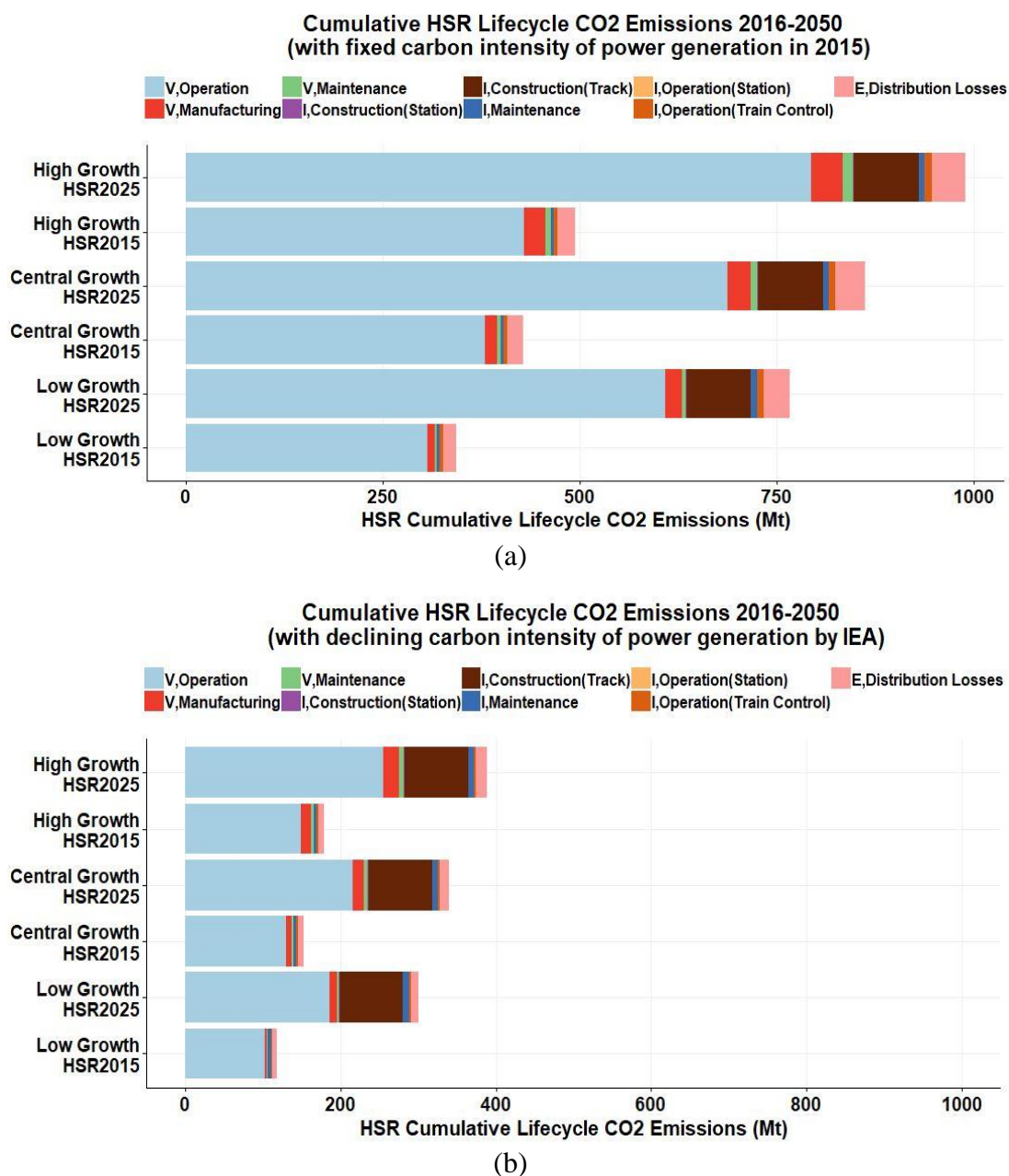


Figure 6-8. Cumulative HSR lifecycle CO₂ emissions between 2016 and 2050, with fixed and declining carbon intensity for power generation.

Figure 6-8 shows the estimated cumulative HSR lifecycle CO₂ emissions under the 2015 and the 2025 network between 2016 and 2050. As described previously, the resulting inventories from a fixed carbon intensity (a) and a declining carbon intensity (b) for power generation are presented separately. The CO₂ emissions of each lifecycle component is calculated and compared between the two carbon intensity scenarios.

As can be seen, with an enhanced network, emissions from the 2025 HSR system could be about twice the levels of the 2015 HSR system across all scenarios. Specifically, compared to the 2015 network, with the fixed 2015 carbon intensity for power generation (Figure 6-8a), the 2025 HSR system is projected to generate about 495 Mt additional CO₂ emissions in a high-growth future, about 454 MtCO₂ in a central-growth future, and about 403 MtCO₂ in a low-growth future. In contrast, if China continues decarbonizing its power generation sector and eventually achieve a zero-carbon electricity production, emissions from HSR system could be greatly reduced (Figure 6-8b). Compared to the 2015 HSR network, only 199 Mt additional CO₂ emissions would be generated from the enhanced 2025 network in a high-growth future, 183 MtCO₂ in a central-growth future, and 171 MtCO₂ in a low-growth future.

Vehicle operation accounts for by far the largest proportion of the total HSR lifecycle emissions but also has the greatest potential to reduce CO₂ emissions through cleaner power generation. For instance, in the high-growth scenario, the 2025 HSR network is projected to generate about 794 MtCO₂ (86% of the total HSR lifecycle CO₂ emissions) from HSR operations with the fixed 2015 carbon intensity, compared to 255 MtCO₂ (66% of the total HSR lifecycle CO₂ emissions) with a declining carbon intensity. On average, it is estimated that 70% operational emissions reduction in HSR could be achieved if China keeps decarbonizing its power generation sector.

Among the non-operational components, infrastructure construction is found to generate most emissions mainly due to material production. Notably, only the 2025 HSR network has the infrastructure construction component because the existing 2015 network does not involve any infrastructure expansion. In addition, since this component is largely independent to electricity consumption, its share of CO₂ emissions remains constant across different scenarios, accounting for about 8-11% of

the HSR lifecycle emissions under the fixed carbon intensity and about 21-28% under the declining carbon intensity. Emissions from electricity T&D losses are also an important contributor to total HSR lifecycle CO₂ emissions, again depending on the carbon intensity for power generation. This component accounts for 3-4% of the total lifecycle emissions in all scenarios. Following the electricity T&D, vehicle manufacturing also has a 2-3% contribution to the lifecycle emissions of HSR. The remaining components, namely vehicle maintenance, infrastructure operation and maintenance only account for a small proportion to the HSR lifecycle CO₂ emissions.

6.5.1.2 Air Transport Lifecycle Emissions

Similar to the HSR estimation, the lifecycle CO₂ emissions for air transport also consists of vehicle (i.e. aircraft manufacturing, operation, and maintenance), infrastructure (infrastructure construction, operation, and maintenance), and fuel production components. In this section, the same bottom-up approach is pursued to estimate the lifecycle CO₂ emissions from the Chinese air transport system using the aviation values provided by Chester (2008). Table 6-5 provides a summary of key values for estimating emissions from each of the aviation lifecycle components.

Air Transport Operational Emissions

Instead of using Chester's estimation directly, fuel burn and CO₂ emissions from aircraft operation (take-off, climb, cruise, descent, landing, and taxi) on a given O-D city pair are estimated using the PIANO-X aircraft performance model (Lissys Ltd, 2017). The PIANO-X model takes into account all important factors that determine aircraft CO₂ emissions, such as aircraft type and size class, load factor, stage length, and total number of flights for each aircraft type operated. Aircraft operational emissions are a major component of the air transport lifecycle CO₂ emissions.

Table 6-5. Emission factors of aviation lifecycle CO₂ emissions components based on Chester (2008).

Category	HCR LCI Component	Calculation based on	Chester(2008)		This study
Aircraft Operation	Taking off, climbing, cruise, approaching, landing, taxing	Emission factors for various aircraft and engine types	Non-cruise emissions: FAA EDMS model (FAA, 2007); Cruise emissions: emission factors of aircraft/engine		the PIANO-X aircraft performance model
Aircraft Manufacture	Aircraft Manufacture	tCO ₂ /plane: Small: 5,100; Med: 17,000; Large: 52,000	Small: 0.13 tCO ₂ /lbs Med: 0.17 tCO ₂ /lbs Large: 0.16 tCO ₂ /lbs		0.15 tCO ₂ /lbs
	Engine Manufacture	tCO ₂ /plane: Small: 1,800; Med: 3,300; Large: 11,000	Small: 0.05 tCO ₂ /lbs Med: 0.03 tCO ₂ /lbs Large: 0.03 tCO ₂ /lbs		0.04 tCO ₂ /lbs
Aircraft Maintenance	Airframe Maintenance	Material Costs(\$/FH): Small: 28; Med: 110; Large: 220	1,762	tCO ₂ /\$million	1,762 tCO ₂ /\$million
	Engine Maintenance	Material Costs (\$/FH): Small: 10; Med: 61; Large: 640	411	tCO ₂ /\$million	411 tCO ₂ /\$million
Infrastructure Construction	Airport Construction	Airports	462	kgCO ₂ /m ²	2.2 m ² /m ² of runway
		Runways	108	kgCO ₂ /m ²	1 m ² /m ² of runway
		Taxiways/Tarmacs	73	kgCO ₂ /m ²	1.3 m ² /m ² of runway
		Parking	24	kgCO ₂ /m ²	0.4 m ² /m ² of runway
Infrastructure Operation	Airport Lighting	Annual electricity consumption	758	kCO ₂ /kWh	29.5 kWh/m ² of runway
Infrastructure Maintenance	Airport Maintenance	5% of the total construction emissions.			
Fuel Production	Jet fuel refining and production	Total costs of jet fuel consumption (\$million)	2,200	tCO ₂ /\$million	Recovery efficiency: 98%; Refining efficiency: 91.1%; 12.185 kgCO ₂ /MMBtu crude oil (GREET)

Air Transport Non-operational Emissions

As shown in Table 6-5, aviation non-operational phases include vehicle components (manufacturing and maintenance), infrastructure components (construction, operation, and maintenance), and fuel production. Detailed estimation procedures are presented below for each non-operational component.

1) Aircraft Manufacturing

In Chester (2008), three representative aircraft are chosen to model the entire U.S. commercial passenger fleet, namely Embraer 145 (small size for short-haul, with 2 engines), Boeing 737-800 (medium size for medium-haul with 2 engines), and Boeing 747 (large size for long-haul, with 4 engines). In contrast, this study uses a much more detailed aircraft size classification based on Sustainable Aviation (2016) (see Appendix A). Thus, the emission factors from the three aircraft sizes for aircraft manufacturing from Chester (2008) are converted into a generic parameter that can be applied to all nine aircraft size classes in this study. As shown in Table 6-4, when computing CO₂ emissions for aircraft manufacturing, the aircraft and its engines are considered separately.

From Chester (2008), emissions from manufacturing are determined by aircraft and engine costs. The estimated emission factors of aircraft manufacturing (excluding engines) are 5,100 tCO₂/plane for small aircraft, 17,000 tCO₂/plane for medium aircraft, and 52,000 tCO₂/plane for large aircraft, respectively. Thus, the CO₂ emissions from manufacturing per lbs of aircraft are calculated for each size of the aircraft used by Chester, as shown in Table 6-5. Given that the tCO₂ per lbs of aircraft is very close, their average value is used as a generic emissions factor of aircraft manufacturing for all the nine aircraft size classes in this study. Similarly, emissions factors estimated by Chester for engine manufacturing are 1,800 tCO₂/plane for small

aircraft, 3,300 tCO₂/plane for medium aircraft, and 11,000 tCO₂/plane for large aircraft, respectively. Based on these emission factors, the average CO₂ emissions per lbs of aircraft generated from manufacturing engine is derived and applied to all aircraft size classes in the estimation.

The number of aircraft required each year is estimated based on the projected annual total flights, the corresponding total flight hours, and average aircraft utilisation rate by aircraft class. Assuming that the proportion of fleet composition remains constant, the total number of aircraft by size class is computed and compared year by year. If the total number of aircraft required in a given year is more than that of the previous year, it indicates that new aircraft are added to the system.

2) Aircraft Maintenance

As shown in Table 6-5, emissions from aircraft maintenance are calculated based on total airframe and engine material costs on a per flight hour basis (Chester, 2008). Thus, similar to vehicle manufacturing, the average airframe and engine material costs per lbs of aircraft is firstly estimated as a generic parameter that can be applied to all aircraft sizes. Following that, the annual maintenance costs by aircraft size class is calculated based on their corresponding annual flight hours. Finally, the respective emissions factors are applied to airframe maintenance at 1,762 tCO₂ per million dollars of airframe material costs, and to engine maintenance at 411 tCO₂ per million dollars of engine material costs.

3) Airport Construction

As discussed in Section 6.4.2, the additional airport capacity needed to meet the projected growing demand under the 2015 and the future planned 2025 HSR network is estimated separately. The total number of additional runways required

between 2016 and 2050 are derived for each Chinese airport under different future scenarios.

According to Chester (2008), 462 kgCO₂ emissions are generated from constructing 1 m² of airport (43 kgCO₂ per ft²), 108 kgCO₂ emissions from constructing 1 m² of runway (10 kgCO₂ per ft²), 73 kgCO₂ emissions from constructing 1 m² of taxiways and tarmacs (6.8 kgCO₂ per ft²), and 24 kgCO₂ from constructing 1 m² of car parking spaces (2.2 kgCO₂ per ft²) (Table 6-5). Using the configuration data of Beijing Capital International Airport (PEK)⁸, it is estimated that constructing 1 m² runway would come with an average of 2.2 m² airport area, 1.3 m² taxiway and tarmac, and 0.4 m² car parking area. Therefore, the new capacity of airports, taxiways and tarmacs, and car parking areas associated with the estimated additional runways are derived. Finally, the corresponding emissions factors for constructing the infrastructure are applied.

4) Airport Operation

Emissions from airport operation mainly result from airport electricity consumption. Again, due to data constraints, I use the annual total electricity consumption of the PEK airport from its annual report in 2015 (BCIA, 2016) and compute the average electricity use per m² of runway. Without considering any efficiency improvements of airport electricity end-use, the parameter is used to estimate yearly total electricity consumption of all existing and estimated new airports between 2016 and 2050. Having estimated the total electricity consumption from airport operation, the emissions factor of power generation in China is applied to obtain CO₂ emissions from airport operations.

⁸ PEK configuration specifics: total area 1.41 million m², 3 runways (3600 m long by 60 m wide), tarmac area 860,000 m², total parking spaces: 9430.

5) Airport Maintenance

Emissions from airport maintenance are assumed to be 5% of airport construction emissions (Chester, 2008). This should cover maintenance for both the existing airports and the estimated additional capacity.

6) Fuel Production

Emissions from producing jet fuels are also included. Both the petroleum recovery efficiency rates and the refining efficiency are obtained from a report on lifecycle emissions of aviation fuels by the GREET model (2012). In addition, emissions from production of jet fuel are based on the Well-to-Pump (WTP) calculator provided by the GREET model (2016).

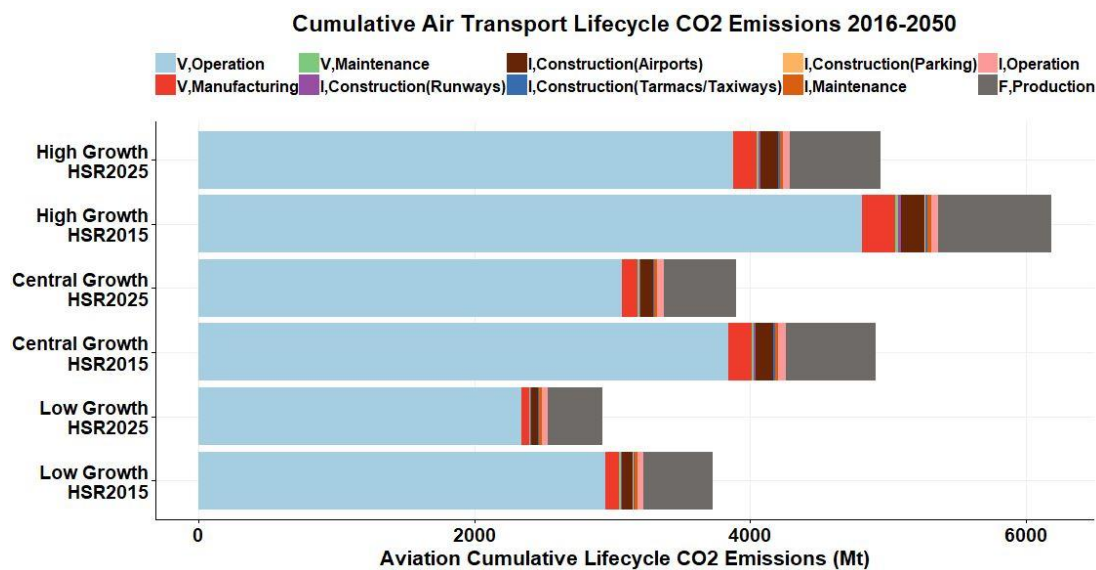


Figure 6-9. Cumulative air transport lifecycle CO₂ emissions between 2016 and 2050, under the 2015 and the 2025 HSR network.

Figure 6-9 shows the cumulative air transport lifecycle CO₂ emissions between 2016 and 2050 under the 2015 and the 2025 HSR network for the three future growth scenarios. As can be seen, with an expanded 2025 HSR network, the cumulative lifecycle aviation emissions are lower across all the future scenarios, compared to the emissions under the 2015 network. Specifically, by expanding the 2015 HSR network

to the 2025 network, a total of 1,236 million tonnes lifecycle CO₂ emissions from air transport will be saved in the high-growth case, 1,014 MtCO₂ be saved in the central-growth case, and 800 MtCO₂ be saved in the low-growth case, respectively.

The largest proportion of the aviation lifecycle CO₂ emissions comes from aircraft operational emissions. The aircraft operation component accounts for 78-80% of the lifecycle aviation CO₂ emissions. Among the non-operational components, jet fuel production has the largest contribution of around 13% of the total, followed by infrastructure construction accounting for about 3-4% and aircraft manufacturing for 2-3% of total lifecycle CO₂ emissions. The remaining components, namely vehicle maintenance, infrastructure operation and maintenance account for the remaining 1-3% of total lifecycle CO₂ emissions.

Having estimated the cumulative lifecycle CO₂ emissions inventories for both HSR and air transport under the current and the future planned HSR network, in the next section, the net lifecycle emissions savings by HSR substitution from expanding the 2015 HSR network to the 2025 network are calculated.

6.5.2 Estimations to Marginal Net Lifecycle Emissions Savings

The previous section estimated the cumulative lifecycle CO₂ emissions of future HSR and air transport systems under the existing 2015 HSR network and the future planned 2025 HSR network, between 2016 and 2050. For HSR, given that the lifecycle assessment is conducted based on the projections for total HSR demand (i.e. diverted demand from aviation and induced demand by HSR), it provides valuable insights to the possible CO₂ emissions generated from the entire system.

In contrast, this section calculates the marginal net lifecycle CO₂ emissions savings from substituting HSR for air transport after HSR network is expanded. In this

case, only the diverted demand from air transport to the expanded HSR network is considered. Specifically, the net emissions savings are derived from two deltas: the “avoided” lifecycle aviation emissions resulted from the diverted demand to HSR, after the 2015 HSR network is expanded to the planned 2025 network, and the “additional” lifecycle HSR emissions of transporting this diverted air demand by HSR. Eq.(6-8) expresses how the marginal net savings ($MNS_{lifecycleCO_2}$) of lifecycle CO₂ emissions are calculated for the diverted demand:

$$MNS_{lifecycleCO_2} = (AirPax_{2015network} - AirPax_{2025network})_{AirLifecycleCO_2} - (AirPax_{2015network} - AirPax_{2025network})_{HSRLifecycleCO_2} \quad (6-8)$$

where $AirPax_{2015network}$ represents total air transport passenger demand under the existing 2015 HSR network, and $AirPax_{2025network}$ is the total air transport passenger demand under the planned 2025 HSR network. Thus, the difference between the two demands is the diverted passengers from air transport to the expanded HSR. The first parentheses then represents the “avoided” lifecycle CO₂ emissions associated with diverted passenger demand; and the second parentheses indicates the “additional” lifecycle CO₂ emissions generated by HSR for transporting the diverted demand from aviation.

6.5.2.1 HSR Lifecycle Emissions for Transporting the Diverted Demand

As Figure 6-4 shows, the diverted aviation demand is the gap between the projected demand under the 2015 and the 2025 HSR network. Thus, the associated “avoided” lifecycle aviation emissions can be directly derived from the aviation lifecycle emissions under the 2015 and the 2025 HSR network estimated from Figure

6-9 for the three future scenarios. In contrast, the associated “additional” HSR lifecycle emissions for transporting the diverted demand needs to be estimated.

The major difference between HSR lifecycle emissions for transporting the diverted demand only and the lifecycle emissions estimated for total HSR demand (diverted demand plus induced demand) in Section 6.5.1.1 lies in the HSR operational phase, where HSR operational emissions for the diverted trips are calculated by replacing the total HSR PKT ($HSR.Pax_{ij} \times HSR.Dist_{ij}$) in Eq. (6-7) by the diverted PKT ($Diverted.Pax_{ij} \times HSR.Dist_{ij}$). In addition, for the non-operational components, because only the diverted demand from aviation is considered, less emissions from train manufacturing and maintenance would be generated as fewer trains are needed for transporting the diverted demand instead of the total HSR demand (diverted passengers plus induced HSR passengers). On the other hand, emissions from the remaining non-operational components, including infrastructure construction, operation, and maintenance, are expected to be the same to the estimations in Section 6.5.1.1, as these infrastructure-related components are not affected by the number of passengers transported by HSR.

In order to estimate the number of trains required for just transporting the diverted passengers from aviation, a few assumptions are made. Firstly, it is assumed that the HSR train type operated on this route remain the same and thus seats available per train are unchanged. Additionally, the utilization rate of transporting the diverted passengers are also assumed to be the average utilization rate on this route. Thus, based on the annual diverted passengers on a given O-D city pair, the annual HSR frequency for just transporting the diverted demand are estimated. Following that, similar to Section 6.5.1.1, assuming a 16 hours’ daily operation, the total number of HSR trains required on a given O-D city pair is estimated based on daily operational frequency

and journey time. Finally, the number of additional trains required on this route is estimated by comparing the number of trains required this year and in the previous year. It is assumed that new trains are manufactured in the year before their operation. Once the number of trains required is estimated, emissions from manufacturing new trains and routine maintenance of existing trains for transporting the diverted passengers are calculated.

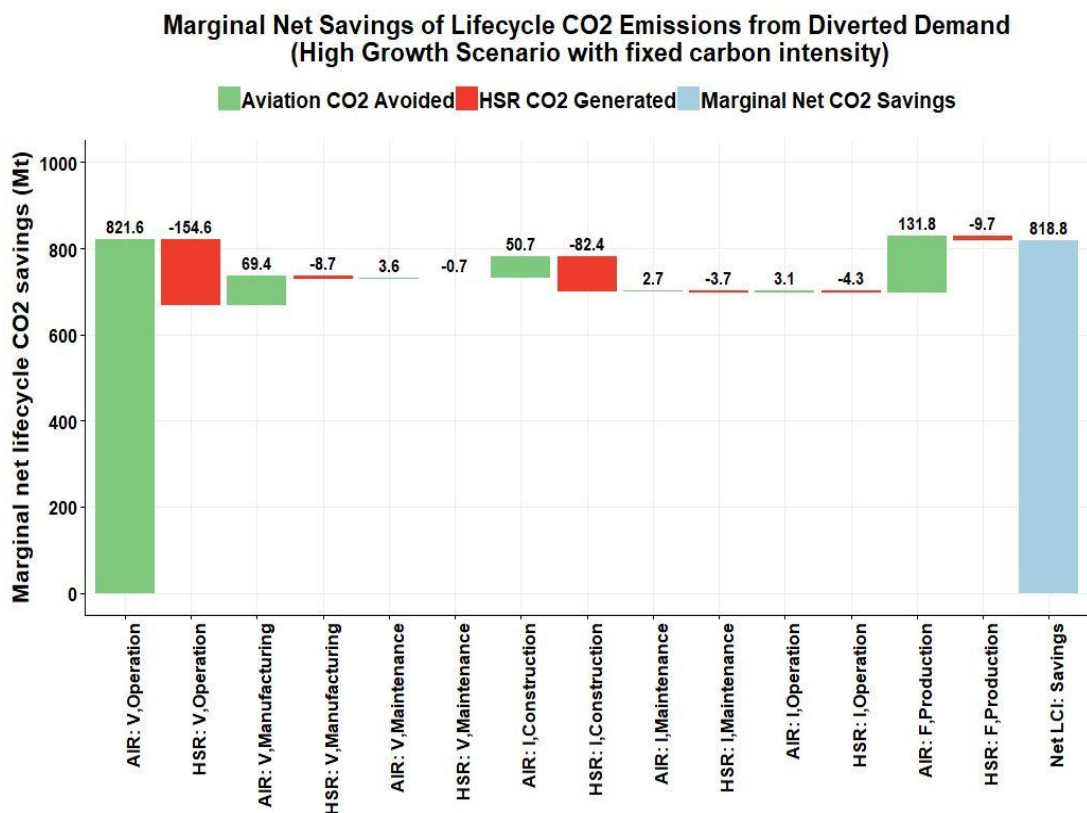
6.5.2.2 Marginal Net Emissions Savings from Transporting the Diverted Demand

Having estimated lifecycle emissions “avoided” from air transport due to the diverted demand to HSR and lifecycle emissions generated from HSR for transporting these diverted passengers, this section calculates the marginal net emissions savings from the diverted demand, based on Eq. (6.8).

Figure 6-10 depicts the estimated marginal net savings of lifecycle emissions with the fixed 2015 carbon intensity at 657 gCO₂/kWh for power generation (IEA, 2017a). As the y-axis depicts the emissions savings, the positive values (green bars) represent the “avoided” or “saved” CO₂ emissions for each of the aviation lifecycle components, after the HSR network is expanded. For example, the very left green bar in the high-growth scenario (Figure 6-10a) indicates that a total of 821.6 MtCO₂ from aircraft operation could be saved between 2016 and 2050 from the diverted air travel passengers to HSR. Correspondingly, the negative values (red bars) represent the “additional” emissions generated by HSR for transporting only the diverted passengers over the 2016 to 2050 period. These numbers are labelled negative because they are cancelling the CO₂ emissions “saved” from air transport. For example, by transporting passengers diverted from air transport, the 2025 HSR system could generate a cumulative of 154.6 million tonnes CO₂ emissions from operation phase alone

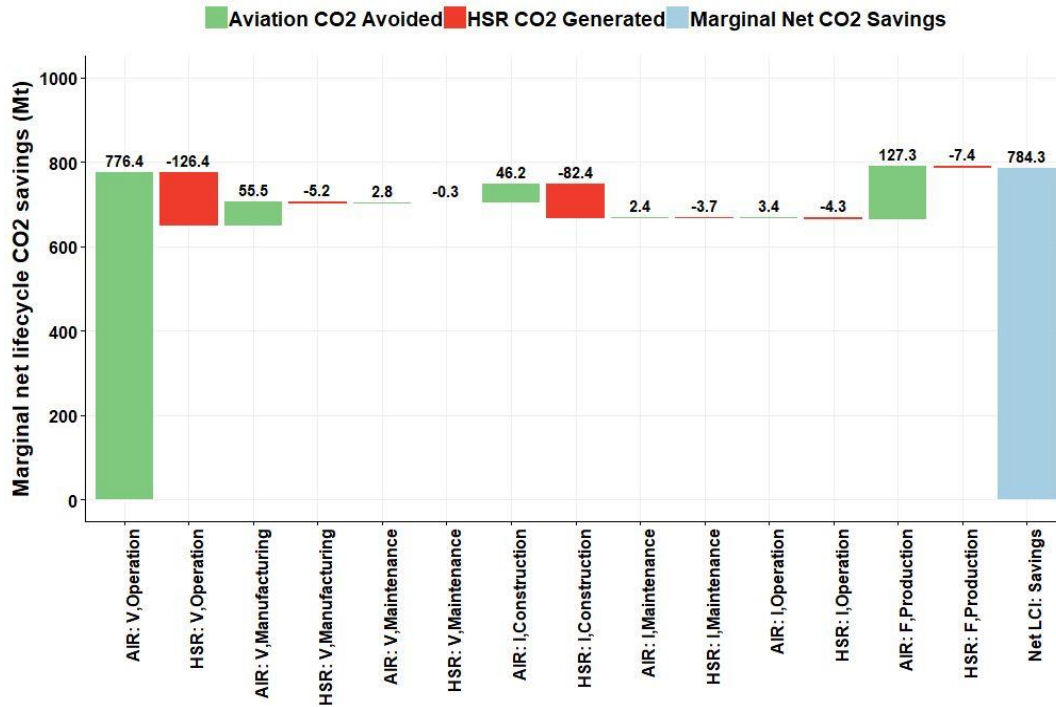
between 2016 and 2050. Thus, the cumulative marginal net emissions savings from vehicle operation alone in this case would be 667 (821.6-154.6) MtCO₂. Finally, the blue bar at the very right is the summation of net marginal emissions savings from HSR substitution over all the lifecycle components on its left, which is the net lifecycle emissions savings from transporting only the diverted air passengers by HSR under the expanded HSR network.

With the three types of bars in Figure 6-10 explained above, the cumulative marginal net savings of lifecycle emissions (blue bars) under the fixed carbon intensity for power generation are estimated to be 819 MtCO₂ in the high-growth scenario, 784 MtCO₂ in the central-growth scenario, and 643 MtCO₂ in the low-growth scenario, respectively. This is equivalent to an annual average marginal net savings of 23 MtCO₂ per year in the high-growth case, 21 MtCO₂ per year in the central-growth case, and 18 MtCO₂ per year in the low-growth case, respectively.



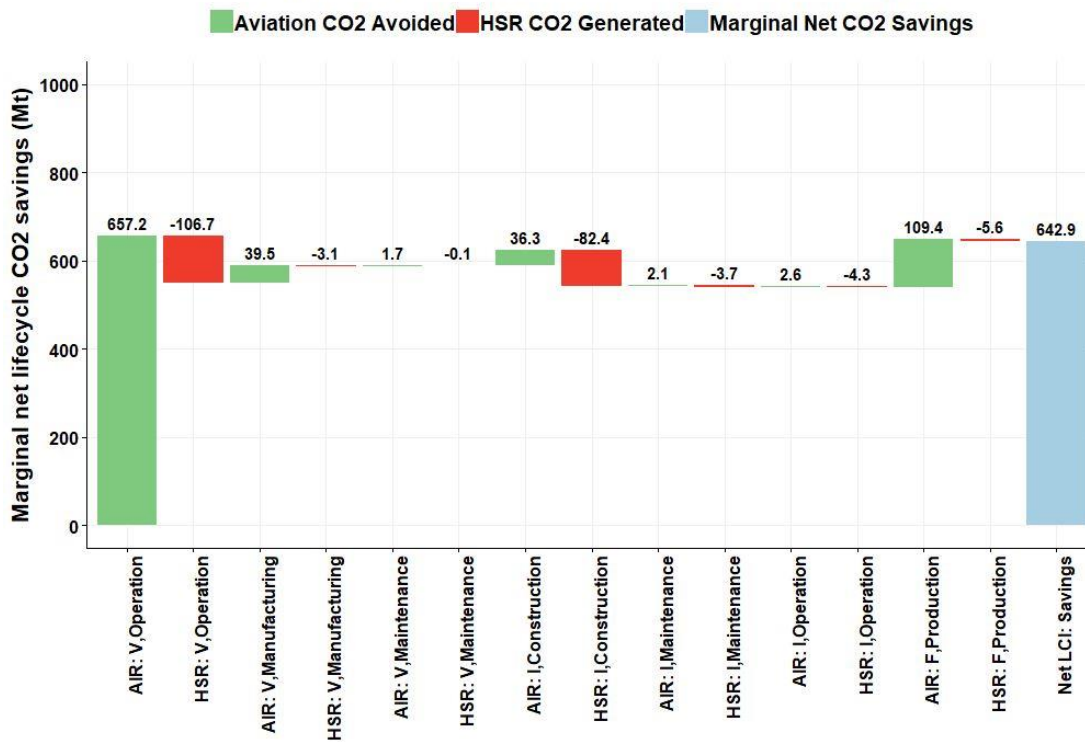
(a)

Marginal Net Savings of Lifecycle CO₂ Emissions from Diverted Demand
(Central Growth Scenario with fixed carbon intensity)



(b)

Marginal Net Savings of Lifecycle CO₂ Emissions from Diverted Demand
(Low Growth Scenario with fixed carbon intensity)

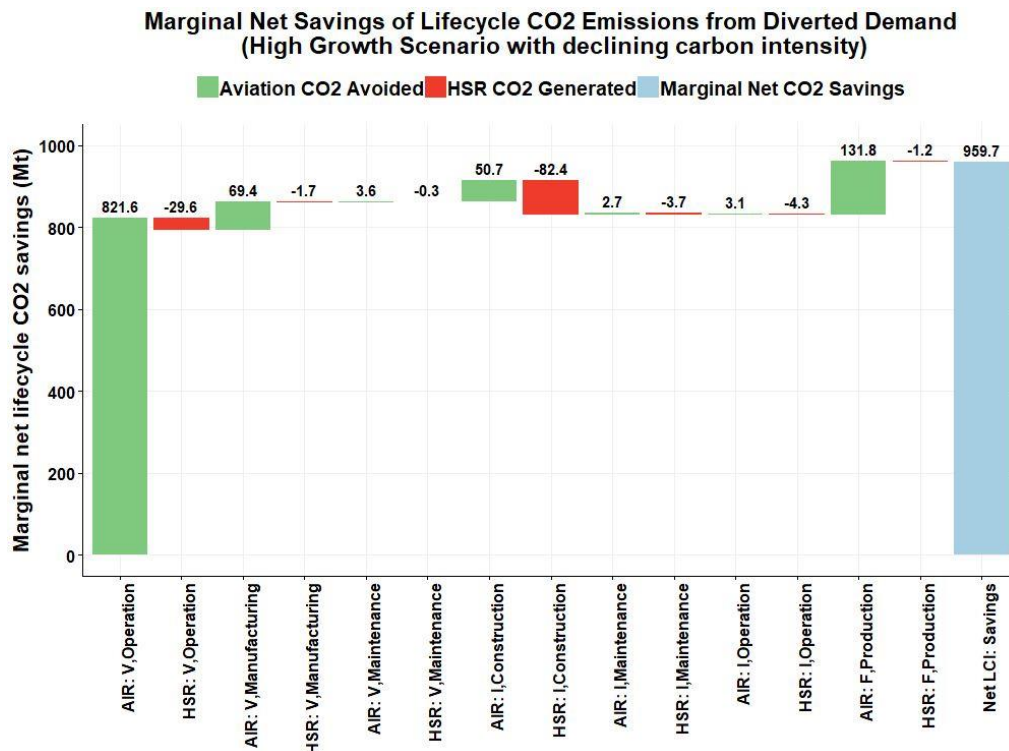


(c)

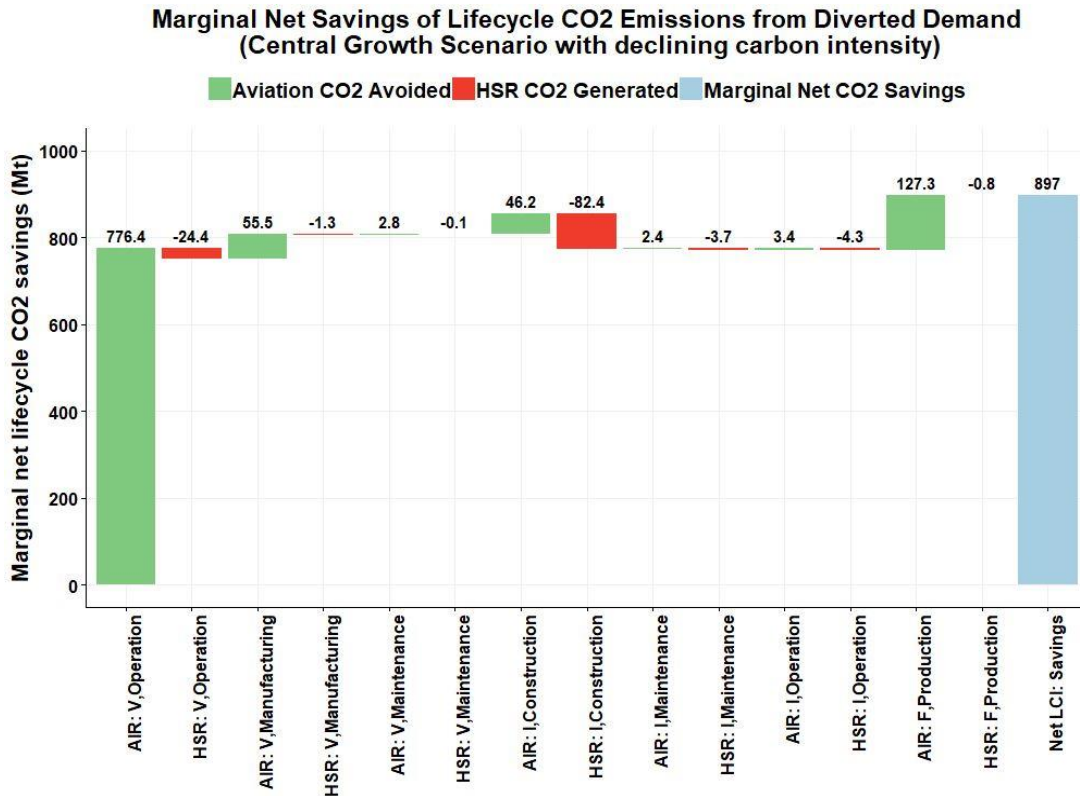
Figure 6-10. Marginal net savings of lifecycle CO₂ emissions from transporting the diverted air passengers by HSR under the 2025 HSR network (2016-2050), with fixed carbon intensity for power generation.

The figure shows that, as HSR has considerably lower energy intensity than air transport, transporting the same number of passengers not by aircraft but by HSR trains could generate about 5-6 times less CO₂ emissions at vehicle operational phase. Notably, this is close to my previous finding in Chapter 2 that HSR is on average about 7 times more energy efficient than aircraft on long-haul routes (see Section 2.3.2). The slightly higher HSR emissions estimated here could be explained by China's high carbon intensity in electricity generation.

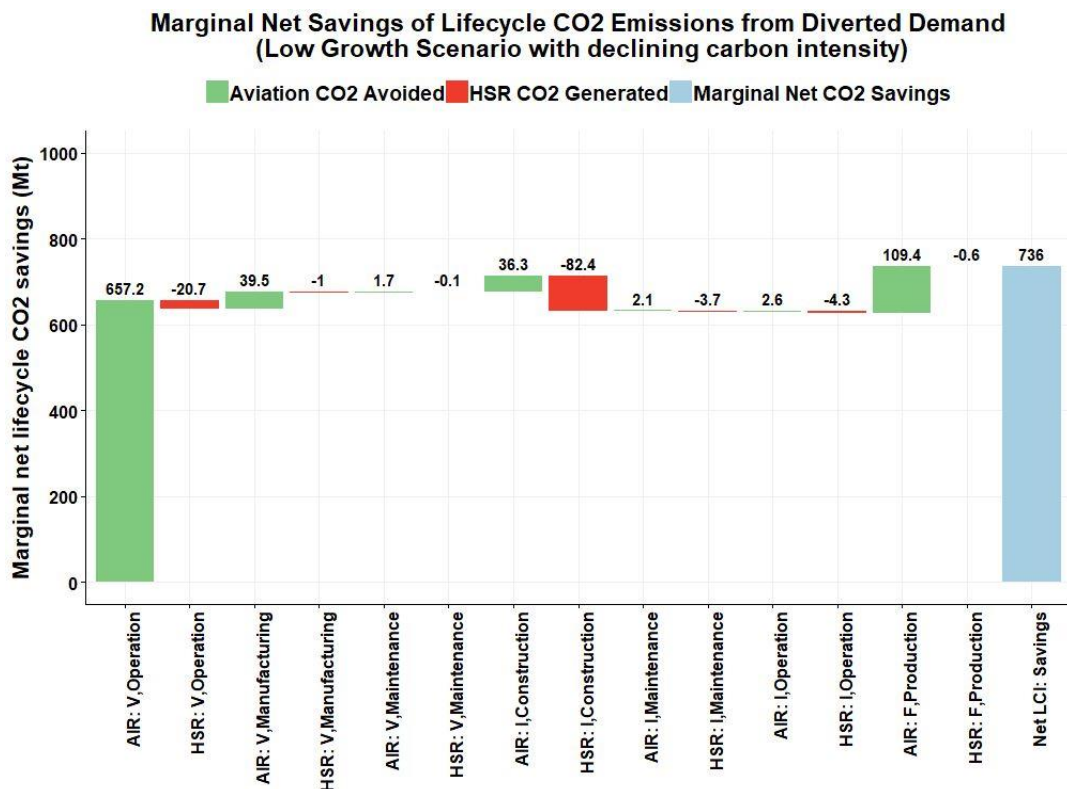
In comparison, it is found that HSR produces slightly more emissions from the infrastructure-related non-operational phases than the air transport system. This may be because compared to the additional capacity required by the aviation system, which is estimated in Section 6.4.2, the planned infrastructure expansion of the 2025 HSR network is larger at scale and its associated emissions are generated at infrastructure construction, operation, and maintenance phases regardless how many passengers (just diverted demand or both diverted and induced demand) take HSR.



(a)



(b)



(c)

Figure 6-11. Marginal net savings of lifecycle CO₂ emissions from transporting diverted air passengers by HSR under the 2025 HSR network (2016-2050), with declining carbon intensity for power generation.

Similarly, Figure 6-11 shows the estimated marginal net savings of lifecycle CO₂ emissions with a declining carbon intensity for power generation (see Figure 6-7). It is assumed that China may continue decarbonizing its power sector and achieve a zero-carbon generation in 2050. Due to the gradually cleaner power generation, the cumulative marginal net lifecycle CO₂ emissions could reach 960 million tonnes in the high-growth scenario, 897 million tonnes in the central-growth scenario, and 736 million tonnes in the low-growth scenario, respectively. The net lifecycle emissions savings are considerably larger than those with the fixed carbon intensity for power generation (Figure 6-10), because all the HSR components (red bars) that involve electricity use (vehicle operation, vehicle manufacturing, vehicle maintenance, infrastructure operation (train control), and electricity T&D losses) would generate significantly smaller amount of “additional” CO₂ emissions with a declining carbon intensity for transporting the diverted demand.

With the declining carbon intensity, the annual average net lifecycle savings between 2016 and 2050 is about 27 MtCO₂ per year (equivalent to 50.2% of the 53.8 million tonnes domestic aviation emissions in 2015) in the high-growth future, 25 MtCO₂ per year (equivalent to 46.5% of the 2015 domestic aviation emissions) in the central-growth case, and 21 MtCO₂ per year (equivalent to 39% of the 2015 domestic aviation emissions) in the low-growth scenario, respectively.

6.6 Conclusions

The large-scale deployment of HSR in China over the past ten years has connected hundreds of city pairs by high-speed trains. As a result, domestic passenger air transport faces increasing competition from HSR. Through developing, estimating

and testing a demand model that projects aviation and HSR demands under the existing 2015 HSR network and the future planned 2025 network, this chapter estimated the possible lifecycle CO₂ emissions of both air transport and HSR systems between 2016 and 2050, and also the marginal net savings of lifecycle emissions resulted from transporting the diverted air passengers by the enhanced HSR.

The demand projections show that, under the expanded 2025 HSR network, domestic air travel demand in China may grow significantly less than the air demand under the existing HSR network. Correspondingly, less capacity expansion would be required in the aviation system to meet the projected demand. Based on these estimations, I assessed the lifecycle CO₂ emissions of both high-speed transport systems under the 2015 and the 2025 HSR network, respectively.

The chapter concludes with an estimation to marginal net savings of lifecycle CO₂ emissions associated with the diverted passengers from air transport to HSR, once the HSR network is expanded. The results show that, through substituting HSR for air transport, the 2025 HSR system could generate a cumulative marginal net lifecycle savings of 736-960 MtCO₂ from low-growth to high-growth future scenarios, if China continues decarbonizing its power sector and achieve a zero-carbon generation in 2050. The annual average net savings are equivalent to 39-50% of the 53.8 MtCO₂ domestic aviation emissions in 2015. However, such emissions saving potential could be considerably compromised by a fixed carbon intensity at 657 gCO₂/kWh. The marginal net savings under this setting would reduce to 643-819 MtCO₂ from the low-growth to the high-growth future, which are equivalent to 34-43% of the 2015 domestic aviation emissions on the annual basis.

Chapter 7 Conclusions

This chapter provides concluding remarks for the dissertation. It starts by briefly reviewing the research conducted in each of the main chapters, including major findings and some key assumptions and limitations associated with the data used in this work. Based upon the findings obtained in each chapter, conclusions can be drawn concerning the research questions that this thesis aims to address as well as important policy implications. This is then followed by a discussion on the contributions from the dissertation to the current body of literature and some further thoughts with respect to the wider implications of the two mitigation strategies. Finally, the chapter concludes with some recommendations for future research.

7.1 Summary of the Work

This dissertation provides a thorough analyses on two important climate change mitigation strategies for passenger air transport. The two strategies consist of market-based measures (MBMs) and the substitution of high-speed rail (HSR) for air transport. The two mitigation strategies studied in this thesis could help policy makers to make informed decisions on adopting them as complementary options to reducing CO₂ emissions from passenger air transport sector. At the beginning of this dissertation, the literature review in Chapter 2 identified a gap in the area of empirically assessing airline cost pass-through behaviour under market-based emissions reduction measures, and in the area of evaluating the potential for mode substitution of HSR for air transport as a system-wide mitigation strategy, with a focus

on China's HSR system. Based on the identified research gaps, specific research questions are formed for each of the main chapters to address.

7.1.1 Chapter 4: Findings, Assumptions, and Limitations

The first research question was regarding the potential impact of market-based emissions reduction measures on airline pricing behaviour. Using the cross-sectional data on itinerary average airfares of all airline markets globally for the year 2015, Chapter 4 developed and estimated an econometric itinerary-based airfare model, which explicitly captures airline operating costs. With a set of other important determinants on airline pricing being controlled for, the airfare model produces cost pass-through elasticities for fuel cost per passenger, non-fuel cost per flight, and non-fuel cost per passenger for different world regions (Table 4-3 and 4-4). A cross-regional and cross-cost-type heterogeneity in cost pass-through is found. For example, the estimated results indicate that in some regional markets (e.g. AP-AP), airlines are more responsive to fuel cost increase whilst in other regions (e.g. most ME-related markets) an increase in non-fuel costs could make a greater impact on airline pricing.

Furthermore, given that each cost component accounts for a varying proportion of airline's total operating costs on a given itinerary, increases in individual cost component may have stronger impact in percentage terms to the cost-related part of fares than its impact to the whole fare price. In order to explore this issue, I conducted an additional analysis where itinerary airfares are broken down into parts that are fuel-related, aircraft-related, and non-fuel-passenger-related. Although this approach "unconventionally" changes the dependent variable into the cost-related part of the fares instead of the observed airfares, important additional insights are found from this exercise (Table 4-5). The significantly larger cost pass-through elasticities estimated

from this setting suggest that a large proportion of increases in a given per-passenger cost is actually passed on to its related part of fares, although this cost pass-through only leads to a small increase in percentage terms in the whole fare price. Moreover, conclusions regarding the cross-region heterogeneity drawn from my main findings still largely stand in this analysis.

Based on the estimated cost pass-through elasticities, the impact of a carbon tax in the European and Asia-Pacific markets are tested (Figure 4-4). Because of the higher fuel cost pass-through elasticity in the Asia-Pacific market, a carbon tax could lead to higher airfares, lower demand, and thus greater emissions reductions in the Asia-Pacific compared to the European market. Specifically, under a “no-intervention” base case, CO₂ emissions in AP-AP and EU-EU could increase by 119-496% and 67-416%, respectively, between 2015 and 2050, depending on specific future growth scenarios. However, if a carbon tax (linearly increases from \$36/tCO₂ in 2015 to \$150/tCO₂ by 2050) is introduced to the global aviation sector, emissions in the two markets may grow slightly slower by 106-431% (AP-AP) and 61-391% (EU-EU).

Despite the useful findings from this chapter, some key limitations requires readers’ attention. Due to the lack of high-frequency time-series data on global airfares, the cost pass-through elasticities are estimated on the cross-sectional data. Thus, the model estimates provide short-run elasticities that may underestimate the effect of increased cost on airfares in the long term. Applying these short-run elasticities in the AIM2015 for long-term projections to 2050 could thus potentially underestimate the possible CO₂ emissions savings from the carbon tax policy. Lastly, the cross-sectional data also makes it not possible to evaluate the potential asymmetric cost pass-through, a topic that has received extensive discussion in the cost pass-through literature.

7.1.2 Chapter 5: Findings, Assumptions, and Limitations

For the second mitigation strategy, i.e. the HSR substitution for air transport, this dissertation takes China's transportation network as a case study. As a first step, Chapter 5 conducted an empirical study that explores how airline supply has already been affected by the introduction of HSR over the period of 2008 to 2015. Through comparing the average seats capacity of domestic Chinese airlines between 2000 and 2015 on routes *with* and *without* the HSR competition on a year-by-year basis, I both graphically (Figure 5-2 to 5-4) and statistically showed that (Table 5-1 to 5-3), from the year that HSR was introduced in the parallel O-D city pair markets, airlines have reduced their seat capacity on the short- (less than 500 km) and stopped adding more capacity on the medium-distance (500-1,000 km) routes. In particular, on the short-distance routes, it is found that airlines do not seem to dramatically reduce their seat capacity right after the HSR entries; rather, the reduction deepens year-after-year as airlines realise that their market share is increasingly taken by HSR on the short-distance markets. This observation is in line with the "lagged response" of travel behaviour (Tsai et al., 2014).

The cumulative operational CO₂ emissions savings from this capacity adjustment by airlines due to HSR substitution are estimated to be 6.52-7.44 million tonnes over the period of 2009 to 2015 (Figure 5-6), depending on assumptions on the electricity intensity of the Chinese HSR trains. This was equivalent to about 12–14% of the 53.8 million tonne domestic aviation emissions in China in 2015. In addition, through a sensitivity analysis that applies a cleaner energy mix to China's electricity generation with the share of coal at 55% (compared with 70% in 2015), I showed that China could have achieved 1.67-2.95 million tonnes additional emissions saving compared to those observed over the same period (Figure 5-8).

One key assumption this analysis is based upon is that all the historical changes in airline seat capacity observed on the affected routes between 2009 and 2015 are the result of the HSR competition. Although my data pre-processing method ensures that HSR substitution could be the dominating force of such changes, airlines may also adjust seat capacity for other possible reasons, such as relatively slow economic development in some cities. In this regard, econometric models such as a Difference-in-Difference (D-in-D) estimation could be an alternative approach that has the capability of controlling for these effects (Wan et al, 2016). In addition, this chapter attempted to estimate the impacts of HSR substitution from supply data for comparing growth rates and forecasting trends. The robustness of this approach could be potentially improved through the use of discrete choice models to predict market shares of both HSR and air transport. However, that would require historical data on passenger flows of both HSR and air transport in China over the sampling period, which is not available to this research.

7.1.3 Chapter 6: Findings, Assumptions, and Limitations

As a second step of assessing the HSR substitution strategy, Chapter 6 explores how the enhanced introduction of HSR may affect future aviation CO₂ emissions in China. To accomplish this objective, a demand model that projects aviation and HSR demands was developed, estimated and tested. The future demand for inter-city high-speed transportation between 2016 and 2050 and the mode shares of HSR and air travel are projected. According to the projections, growth of air passenger flows between 2016 and 2050 is expected to be smaller once the HSR network is expanded in 2025. Correspondingly, less capacity expansion would be required in the aviation system to meet the future demand, compared to the 2015 HSR network. Based on these

estimations, I assessed possible cumulative lifecycle CO₂ emissions for the future HSR and aviation systems in China (Figure 6-8 and 6-9), under the 2015 and the 2025 HSR network. It is found that with an enhanced network, emissions from the 2025 HSR system could be about twice the levels of the 2015 HSR system across all scenarios, whilst aviation emissions under the 2025 HSR network are projected to be lower than the emissions under the 2015 network across all future scenarios.

Finally, I also estimated the marginal net savings of lifecycle CO₂ emissions from HSR substitution. Specifically, the marginal net savings are calculated from the “avoided” lifecycle aviation emissions resulted from the diverted demand to HSR and the “additional” lifecycle HSR emissions of transporting this diverted air demand by HSR. The results show that, if China continues decarbonizing its power sector and achieve a zero-carbon generation in 2050, through substituting HSR for air transport, the 2025 HSR system could generate a cumulative marginal net savings at 736-960 MtCO₂ from 2016 to 2050, depending on the growth scenario in future population, income, and jet fuel prices. However, the marginal net savings could be considerably compromised by a carbon-intensive electricity production.

Similar to Chapter 4, the econometric demand model developed in this chapter is based on the cross-section data of HSR and air transport demand in 2015. This limitation due to data availability makes it less ideal to use the short-run elasticities estimated from the model to the temporally evolving projections for a long-term future. According to Oum et al (1992), the long-run demand is more elastic than short-run demand because travellers have more options to change their travel behaviour in the long run as compared to the short-run. Thus, changes in fare, journey time, or service frequency of one high-speed transport mode may have larger long-term impacts to the demand of the other transport mode, compared to what I projected in this chapter.

7.2 Contributions and Further Thoughts

Perhaps the most important contribution from this dissertation is that it quantitatively measured potential for and the effectiveness of the two strategies that have been poorly assessed in the existing research on climate change mitigation for passenger air transport. Based upon the findings of each main chapter discussed in the previous section, several specific contributions have been made in analysing each of the two mitigation strategies.

For the market-based emissions reduction strategy, a major contribution of this research to existing knowledge is that it estimates the cost pass-through elasticities of airline operating costs for different regional markets. To the best of my knowledge, this is one of the first studies that provides empirical evidence of airlines' cost pass-through behaviour at a global scale. As mentioned earlier, although the fare model is estimated on the cross-sectional data and thus provides short-run cost pass-through elasticities, which might underestimate the cost pass-through in the long run, empirical findings from this work still have a valuable contribution to the existing literature where there is very limited evidence of cost pass-through for the airline sector. In particular, the estimated cost pass-through elasticities to both the whole fare price and the specific cost-related parts of fares could be used in future research that otherwise would have to rely on presumed cost pass-through rates when evaluating the system-wide impacts of MBMs that increase airline fuel cost in the aviation sector.

The second contribution from this work is that it enables testing the potential effects of increasing various types of airline operating costs through market-based measures, such as an increase in fuel costs versus an increase in aircraft' landing charges. With the estimated cost pass-through elasticities for three distinct types of

operating costs, such comparative study could be analysed further. The final key contribution from this part is that it has demonstrated to policy makers that a global market-based environmental policy in aviation may receive different mitigation outcomes by regional market given airlines' distinct sensitivity to increases in specific operating costs. For example, based on my empirical evidence, increasing airline fuel costs could achieve larger emissions reduction impacts in Asia-Pacific market, whilst for the Middle East-involved markets, such policy may have little influence to airline pricing; in contrast, increasing aircraft landing charges at airports might be a more effective approach to impact airlines in these markets.

Results from Chapter 5 and 6 that assess the second mitigation strategy, i.e. the substitution of high-speed rail (HSR) for air transport, also made several contributions to the existing research. From the modelling approach aspect, Chapter 5 provides a novel method to empirically estimate the operational emissions savings from the reduced aviation supply due to the HSR substitution effects. It firstly matches airline supply on routes with and without HSR competition on a year-by-year basis and then simulates airline annual seat capacity on the affected routes assuming no adoption of HSR. This method differs itself from existing approaches that either address the HSR effects as a dummy variable or includes HSR in discrete choice models as an alternative. From the system-wide evaluation perspective, Chapter 6 enriched the current literature by presenting a comprehensive CO₂ emissions lifecycle assessment for the Chinese air transport and HSR systems, taking into account the competition effects between HSR and aviation. The marginal net savings of lifecycle emissions from the expanded 2025 HSR network reported in this dissertation provide useful insights with respect to the climate impact of China's transport infrastructure development in the future. In addition, findings from this chapter also have

implications to other developing countries that seek to develop an energy-efficient transportation system. Finally, both Chapter 5 and Chapter 6 have illustrated the importance of decarbonizing the power generation sector in achieving greater net emissions savings from the HSR modal substitution. Through a comparative analysis between the net emissions saving under the current power generation with high carbon intensity and the possible future power generation with significantly cleaner energy mix, my results suggest that decoupling CO₂ emissions from transportation is not an isolated task but relies on progress of decarbonizing other energy systems as well.

Apart from the contributions discussed above, there are some further thoughts with respect to my findings. Clearly, the two mitigation measures assessed in this dissertation could work together to achieve as much CO₂ emissions savings as possible. In fact, their mitigation effects are expected to compensate with each other nicely based on my findings. Chapter 5 demonstrates that HSR substitution mainly affects the short- and medium-distance routes whereas it can barely impact airlines on the long-haul routes. Therefore, policy makers could consider HSR substitution as the major mitigation strategy for air transport emissions on the short- and medium-distance markets. On the other hand, as the HSR substitution strategy may barely work on the long-haul routes, to limit aviation CO₂ emissions in the long-distance markets, the market-based measures could play a more important role instead. As such, the two mitigation strategies could effectively cover both the short- and medium-range markets and the long-haul markets. However, on the long-distance routes, although the competition from HSR is less severe, airlines are facing higher within-sector competition, which might influence the effectiveness of emissions mitigation by MBMs on the long-haul markets. As demonstrated from the policy simulation in Chapter 4, MBMs could achieve emissions reduction mainly through increased

airfares resulting from airlines' cost pass-through; with the increased fares, air travel demand could grow less rapidly, so as slower growth of aviation CO₂ emissions. When consider adopting MBMs as the major mitigation strategy in long-haul markets, policy makers are suggested to selecting the most effective type of MBMs (e.g. carbon tax, ETS, airport charges on aircraft or passengers, etc.) based on the market structure of local long-distance airline markets (e.g. the number of competing airlines and presence of LCCs) and the estimated cost pass-through elasticities by cost type for their own region, which are provided by this research.

Although the focus of this dissertation is the emissions reduction strategies for passenger air transport, it may also have implications to the air freight business as a significant amount of cargo is often carried in the passenger aircraft. For example, in Hong Kong, between 55% and 60% of air freight is carried in the belly compartment of passenger aircraft (Hong & Zhang, 2010). Air freight carried in a passenger aircraft affects airline operating costs mainly because of the additional weight it adds to aircraft, resulting in more fuel burn during aircraft operation. On the other hand, for the mixed passenger/cargo airlines, cargo revenue accounts for a significant proportion of their total revenue. According to Hong and Zhang (2010), on average, cargo revenue accounts for about 36.2% of the top-10 mixed passenger/cargo airlines.

Therefore, if taking into account the airfreight business, the cost pass-through analysis in Chapter 4 might be affected in different ways. Firstly, and perhaps the most importantly, if airlines believe that passenger demand of their serving markets is relatively elastic and an increase in fares due to cost pass-through would significantly affect demand and therefore their market shares, then having cargo as the other revenue source could help them to hedge the effect of MBMs. Specifically, airlines could absorb the increased cost by their cargo revenue so that passengers would not

be affected by increased fares. This way, the larger share of airlines' revenue, i.e. the passenger revenue, would not be affected; alternatively, they could also split the cost pass-through between passengers and their airfreight customers. Regardless which option is selected, the cost pass-through estimated in Chapter 4 may decrease. On the other hand, if passenger demand is relatively inelastic, the estimated cost pass-through would be less affected by taking airfreight into account. This is because under this circumstance, demand is not expected to drop a lot even if the increased cost is fully passed through onto passengers. As such, airlines do not have to take any revenue loss, and there is also no need to split the increased cost between passengers and airfreight customers.

7.3 Recommendations to Future Research

The research work in this dissertation could be readily built upon or improved by further analysis. Recommendations for future research are briefly summarized below.

Airline-specific Cost Pass-through Estimation

The cost pass-through elasticities estimated in Chapter 4 are based on average airfares and operating costs at a route level. This is mainly constrained by the data availability on airline operating costs. The work however can be potentially improved by estimating the airline-specific cost pass-through elasticities at least for all airlines in the domestic U.S. market, where the complete airline operating costs are publicly available from the DOT Form 41 databases as described in Chapter 2. Such research attempts have been made by Doyme et al. (2019) and proved to be feasible. The improved resolution on the cost pass-through will allow interesting comparison of

potential pricing responses on the MBMs across different airlines, especially between the legacy carriers and LCCs.

Testing on the Effects of Different Types of MBMs

As mentioned in the contribution section earlier, given that the cost pass-through elasticities are estimated for three types of airline operating costs, namely the fuel cost per passenger, the non-fuel cost per passenger, and the non-fuel cost per flight, further analysis can be conducted to compare possible outcomes of MBMs that increase airline's fuel costs, non-fuel passenger costs (e.g. passenger landing fees), and non-fuel flight costs (e.g. aircraft landing costs), respectively. Essentially, such work will provide policy makers greater flexibility in designing and evaluating different forms of MBMs for the aviation sector in the future.

HSR and Aviation Lifecycle CO₂ Emissions Assessment Updates

With respect to the HSR substitution policy part, a key area for potential improvements is on the lifecycle CO₂ emissions estimation. As can be seen from Chapter 6, due to data constraints, this dissertation has heavily relied on the emissions factors and lifecycle emissions values from Chester (2008). Although efforts have been made to replace Chester's value by the China-specific settings wherever possible, it would be valuable to develop a lifecycle accounting software similar to the SimaPro used by Chester (2008) that is specifically for China. With such lifecycle assessment software, future research could improve the accuracy of the lifecycle CO₂ emissions of both HSR and air transport systems in China and re-evaluate the potential net lifecycle emissions savings from the HSR substitution for aviation.

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Appendix A: Aircraft size classes used in this dissertation

This dissertation uses nine aircraft size classes adapted from the Sustainable Aviation (2015) aircraft categories. Aircraft are assigned to classes based on number of seats and MTOW. Each size class category has a reference aircraft.

Size Category	Approx. seat range	Reference aircraft	Reference engine
1. Small regional jet	30-69	CRJ 700	GE CF34 8C5B1
2. Large regional jet	70-109	Embraer 190	GE CF34 10E6
3. Small narrowbody	110-129	Airbus A319	V.2522
4. Medium narrowbody	130-159	Airbus A320	CFM56-5B4
5. Large narrowbody	160-199	Boeing 737-800	CFM56-7B27
6. Small twin aisle	200-249	Boeing 787-800	GENx-1B67
7. Medium twin aisle	250-299	Airbus A330-300	Trent 772B
8. Large twin aisle	300-399	Boeing 777-300ER	PW4090
9. Very large aircraft	400+	Airbus A380-800	EA GP7270

Appendix B: Percentage of direct, one-stop, and two-stops itineraries in each regional market estimated by the airfare model

Market	Total itineraries	Direct routes (%)	One-stop routes (%)	Two-stops routes (%)
AF-AF	1,579	20.6	67.2	12.2
AP-AP	14,786	30.1	65.5	4.4
CA-CA	1,182	26.9	68.3	4.8
EU-EU	19,364	30.4	69.2	0.4
ME-ME	579	54.1	45.8	0.1
NA-NA	53,207	6.6	86.4	7.0
SA-SA	2,775	19.3	69.5	11.2
AP-EU	11,940	3.5	81.1	15.4
AP-NA	6,312	4.6	56.1	39.3
EU-NA	10,783	2.9	83.5	13.6
EU-SA	2,656	1.4	64.7	33.9
CA-NA	7,717	9.2	90.1	0.7
AF-EU	3,640	11.5	79.2	9.3
NA-SA	2,480	2.4	79.8	17.8
CA-EU	1,636	3.2	73.4	23.4
CA-SA	1,084	4.8	74.2	21.0
EU-ME	3,849	23.2	76.5	0.3
AF-AP	1,766	1.3	68.4	30.3
AF-NA	1,010	2.6	66.7	31.7
AP-ME	2,680	20.5	77.2	2.3
ME-NA	1,626	1.2	61.1	37.7
AF-ME	624	30.3	68.2	1.4

Appendix C: Coefficients of the airfare model for all intra-regional markets

Variables	NA-NA Market		EU-EU Market		AP-AP Market		SA-SA Market		CA-CA Market	
	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.
Intercept	0.462***	8.001	3.061***	26.515	2.459***	19.209	-2.284***	-6.931	3.319***	8.282
FuelCostPerPax	0.258***	63.192	0.204***	23.621	0.363***	35.038	0.237***	11.516	0.202***	4.797
NonFuelFltCost	0.147***	45.302	0.071***	8.544	0.232***	23.231	0.363***	16.36	0.146***	6.387
NonFuelPaxCost	0.169***	23.602	0.059***	6.865	0.120***	8.568	0.236***	3.869	0.185***	3.639
ln(Frequency)	0.009***	8.066	0.057***	24.592	-0.002	-0.855	0.014**	3.176	0.017*	1.998
ln(Passengers)	-0.047***	-44.533	-0.066***	-27.946	-0.024***	-10.36	-0.025***	-5.551	-0.031***	-3.465
ln(Load Factor)	0.038***	5.87	0.097***	5.638	0.093***	5.701	0.222***	7.017	0.001	0.031
ln(Average CUI)	0.011***	6.899	-0.011**	-2.802	0.101	0.084	0.014*	2.307	0.055***	4.512
ln(Airport HHI)	0.074***	26.233	0.010*	2.037	0.006	0.867	0.163***	7.592	0.074***	4.183
ln(Route HHI)	0.18***	66.03	0.039***	7.292	0.014*	2.388	0.061***	4.417	0.036	1.582
ln(Route share)	0.07***	71.802	0.046***	23.881	0.031***	12.95	0.023***	4.981	0.068***	10.209
Number of legs = 2	-0.328***	-47.724	-0.144***	-11.663	-0.028*	-2.905	-0.316***	-8.489	0.042	1.386
Number of legs = 3	-0.397***	-36.365	0.021	0.361	-0.054*	-2.335	-0.536***	-9.772	0.251***	5.304
Hubs passed = 1	0.123***	58.755	0.013**	3.032	0.004	0.721	-0.074***	-4.622	-0.114***	-6.595
Hubs passed = 2	0.183***	70.566	0.031***	4.65	0.059***	6.869			-0.198***	-5.165
Hubs passed = 3	0.216***	27.448	-0.005	-0.162	0.142***	7.673				
Hubs passed = 4	0.022	0.192								
Fixed Effects interacted with LCC dummy variable	17		1,672		1,057		121		360	

Observations	53,207	19,364	14,786	2,775	1,182
R ² / Adjusted R ²	0.630 / 0.630	0.617 / 0.608	0.905 / 0.898	0.921 / 0.917	0.929 / 0.897

Variables	AF-AF Market		ME-ME Market	
	Coefs.	t-stats.	Coefs.	t-stats.
Intercept	4.278***	7.478	0.858	1.024
FuelCostPerPax	0.140***	4.897	0.092	1.236
NonFuelFltCost	0.251***	5.197	0.561***	6.954
NonFuelPaxCost	0.102*	2.246	0.435**	2.963
ln(Frequency)	0.022**	3.156	0.071***	3.797
ln(Passengers)	-0.035***	-4.236	-0.061**	-3.218
ln(Load Factor)	0.216***	4.232	0.079	0.671
ln(Average CUI)	-0.001	-0.048	-0.202***	-7.048
ln(Airport HHI)	0.121**	3.282	0.135**	2.773
ln(Route HHI)	0.044	1.39	-0.042	-0.903
ln(Route share)	0.04***	4.192	0.111***	5.72
Number of legs = 2	0.061.	1.708	-0.08	-0.709
Number of legs = 3	0.112*	1.988		
Hubs passed = 1	0.178***	7.464	0.205*	2.051
Hubs passed = 2	0.41***	6.739	0.015	1.024
Hubs passed = 3				
Hubs passed = 4				
Fixed Effects interacted with LCC dummy variable	686		149	
Observations	1,579		579	
R ² / Adjusted R ²	0.947 / 0.904		0.886 / 0.869	

Note: *** Significant at the 0.1% level; ** Significant at the 1% level; * Significant at the 5% level.

Appendix D: Coefficients of the airfare model for all inter-regional markets

Variables	AP-EU Market		AP-NA Market		EU-NA Market		AP-ME Market		AF-EU Market	
	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.
Intercept	1.516***	6.955	1.345***	4.195	1.269***	4.842	2.56***	8.490	5.155***	12.777
FuelCostPerPax	0.235***	11.890	0.209**	9.002	0.193***	6.341	0.087**	2.959	0.113***	4.348
NonFuelFltCost	0.221***	12.884	0.346***	11.409	0.252***	10.407	0.271***	12.084	0.233***	9.791
NonFuelPaxCost	0.165***	13.321	0.268***	13.299	0.125***	6.701	0.145***	4.802	0.069*	2.557
ln(Frequency)	0.064***	19.207	0.006	1.313	0.057***	16.553	0.029***	6.464	0.065***	10.855
ln(Passengers)	-0.040***	-11.760	-0.054***	-11.628	-0.069***	-14.301	-0.046***	-8.838	-0.058***	-8.317
ln(Load Factor)	-0.090**	-3.222	-0.216***	-4.781	-0.19***	-5.325	0.073*	2.118	-0.067	-1.443
ln(Average CUI)	0.009	0.878	0.123***	7.761	0.081***	6.302	-0.044***	-4.679	-0.001	-0.051
ln(Airport HHI)	0.043***	4.448	0.061***	5.511	0.141***	15.142	0.027	1.612	0.065***	3.351
ln(Route HHI)	0.001	0.147	0.069***	5.853	0.164***	14.625	0.058***	4.323	-0.094***	-4.751
ln(Route share)	0.057***	16.718	0.087***	17.620	0.092***	21.775	0.049***	10.112	0.073***	10.911
Number of legs = 2	-0.428***	-25.316	-0.383***	-13.795	-0.262***	-11.031	-0.096**	-3.183	-0.252***	-8.304
Number of legs = 3	-0.621***	-25.602	-0.613***	-16.569	-0.578***	-10.369	-0.224***	-4.191	-0.322***	-7.101
Hubs passed = 1	0.053***	5.094	0.088***	4.852	0.019*	0.804	0.009	0.819	0.051**	2.752
Hubs passed = 2	0.084***	7.065	0.129***	6.691	0.039*	1.618	0.118***	6.740	0.076**	3.142
Hubs passed = 3	0.049**	3.155	0.190***	8.731	0.095***	3.557	0.023	0.753	0.118**	3.102
Hubs passed = 4	-0.081.	-1.938	0.111.	1.921	-0.078	-0.452				

Fixed Effects interacted with LCC dummy variable	1,294	120	176	463	749
Observations	11,940	6,312	10,783	2,680	3,640
R ² / Adjusted R ²	0.797 / 0.772	0.606 / 0.595	0.543 / 0.532	0.927 / 0.911	0.886 / 0.855

Variables	CA-NA Market		AF-AP Market		EU-ME Market		EU-SA Market		NA-SA Market	
	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.	Coefs.	<i>t</i> -stats.
Intercept	1.665***	10.057	3.909***	8.237	0.585	1.597	2.676***	4.296	0.413	0.637
FuelCostPerPax	0.292***	24.568	0.222*	2.152	0.089**	2.934	0.288***	6.983	0.134**	6.588
NonFuelFltCost	0.088***	8.442	0.397***	14.011	0.465***	18.576	0.247***	5.694	0.363***	7.967
NonFuelPaxCost	0.084***	3.687	0.115*	2.504	0.084***	3.619	0.052*	2.013	0.095***	7.511
ln(Frequency)	0.003	1.331	0.022**	2.868	0.046***	8.674	0.075***	11.125	0.003	0.384
ln(Passengers)	-0.028***	-10.537	-0.057***	-7.141	-0.056***	-9.17	-0.012**	-3.514	-0.036***	-4.547
ln(Load Factor)	0.286***	14.092	0.005	0.088	0.115*	2.317	-0.207*	-2.577	0.054	0.695
ln(Average CUI)	0.001	0.111	0.037*	2.004	-0.02*	-1.85	0.007	0.411	-0.068**	-2.994
ln(Airport HHI)	0.022***	3.803	0.114***	3.866	-0.026	-1.781	0.141***	6.694	0.081**	3.234
ln(Route HHI)	0.127***	20.152	-0.009	-0.372	-0.042**	-2.611	0.149***	8.331	0.413***	16.679
ln(Route share)	0.058***	25.374	0.076***	9.994	0.066***	13.073	0.055***	8.059	0.031***	3.565
Number of legs = 2	-0.101***	-6.281	-0.127**	-2.77	-0.318***	-11.662	-0.262***	-7.012	0.040	0.801
Number of legs = 3	-0.138**	-2.856	-0.177**	-2.742	-0.311.	-1.904	-0.363***	-6.818	0.168*	2.214
Hubs passed = 1	0.054***	9.149	0.015	0.897	0.034**	2.644	-0.173***	-5.091	0.161***	7.224
Hubs passed = 2	0.107***	15.195	0.107***	4.61	0.068***	3.856	-0.184***	-4.975	0.307***	11.757
Hubs passed = 3	0.195***	9.364	0.151***	4.338	-0.156	-1.265	-0.369*	-2.155	0.160	0.728
Hubs passed = 4										
Fixed Effects interacted with LCC dummy variable	220		429		673		267		69	
Observations	7,717		1,766		3,849		2,656		2,480	

R ² / Adjusted R ²	0.684 / 0.671	0.848 / 0.827	0.893 / 0.870	0.622 / 0.607	0.635 / 0.619
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Variables	ME-NA Market		AF-ME Market		CA-EU Market		AF-NA Market		CA-SA Market	
	Coefs.	t-stats.	Coefs.	t-stats.	Coefs.	t-stats.	Coefs.	t-stats.	Coefs.	t-stats.
Intercept	4.644***	6.844	0.693	0.855	-2.115**	-3.210	2.522**	2.883	1.346	1.497
FuelCostPerPax	-0.101	-1.953	0.144*	2.098	0.227***	5.501	0.224**	3.324	0.297***	4.111
NonFuelFltCost	0.422***	7.056	0.234***	4.505	0.283***	5.299	0.247***	4.708	0.235***	4.169
NonFuelPaxCost	-0.007	-0.204	-0.137	-0.878	-0.002	-0.042	0.220**	3.185	0.112**	3.882
ln(Frequency)	0.035***	3.978	0.043**	3.165	0.035***	4.074	0.038**	3.021	0.029**	2.841
ln(Passengers)	-0.011*	-2.064	-0.074***	-4.329	-0.05***	-5.072	-0.022	-1.618	-0.07***	-6.785
ln(Load Factor)	-0.216**	-2.672	0.304**	3.26	0.016	0.232	0.277**	2.622	0.166	1.643
ln(Average CUI)	-0.067**	-2.892	0.001	0.037	0.199***	8.608	-0.191***	-5.456	0.031	1.295
ln(Airport HHI)	-0.051*	-2.444	0.23***	3.984	0.149***	6.055	-0.029	-1.113	0.030	0.819
ln(Route HHI)	-0.084**	-2.728	-0.032	-0.775	0.322***	12.247	0.013	0.346	-0.029	-0.904
ln(Route share)	0.098***	10.444	0.102***	6.179	0.082***	8.208	0.090***	7.014	0.102***	9.444
Number of legs = 2	-0.051*	-0.996	-0.181**	-2.769	0.021	0.404	-0.281***	-3.368	-0.349***	-5.211
Number of legs = 3	-0.145*	-1.765	-0.217.	-1.725	-0.036	-0.457	-0.434***	-3.610	-0.578***	-5.608
Hubs passed = 1	-0.005	-0.094	0.045	1.458	-0.12**	-3.198	0.202**	2.688	-0.038	-1.287
Hubs passed = 2	0.017	0.317	0.132*	2.112	-0.113*	-2.552	0.340***	4.326		
Hubs passed = 3	0.073	1.135	-0.194	-1.233	-0.134*	-2.337	0.441***	5.029		
Hubs passed = 4										
Fixed Effects on O-D country pair	45		249		332		96		235	
Observations	1,626		624		1,636		1,010		1,084	
R ² / Adjusted R ²	0.636 / 0.622		0.880 / 0.861		0.686 / 0.651		0.649 / 0.635		0.804 / 0.772	

Note: *** Significant at the 0.1% level; ** Significant at the 1% level; * Significant at the 5% level.