EMPIRICAL ESTIMATION OF AVIATION'S SOCIAL BENEFITS

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Empirical Estimation of Aviation's Social Benefits

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Air transport has long been acknowledged as a critical driver for social and economic development, improving connectivity and accessibility across regions and nations. While its contributions to economic growth and employment have been extensively studied by economists, this thesis broadens the scope by examining two benefits of air transport: its role in promoting bilateral service trade at the national level and its impact on reducing firm-level emissions at the city level. Additionally, this thesis explores the performance of the aviation system during unprecedented disruptions, such as the COVID-19 pandemic. The thesis is organized into three core chapters, each focusing on a distinct aspect of air transport's social benefits.

Chapter 2 examines the aviation sector during crises, specifically analyzing the impacts of the COVID-19 pandemic on airline route choices and the operations of multi-airport systems (MASs). Focusing on the Chinese domestic market, study 1 empirically assesses the pandemic's effects on airlines' route service choices and market interactions from 2019 to 2022. Study 1 estimates an airline route choice model for both full-service carriers (FSCs) and Spring Airlines, China's largest low-cost carrier (LCC). The findings indicate that Spring Airlines has actively expanded its network to all types of routes, particularly those connecting major airports. FSCs also adjusted their route entry strategy by entering more thin routes connected to secondary cities. The pandemic has broken the equilibrium of network differentiation between FSCs and Spring Airlines in China. Spring Airlines has begun expanding services at FSCs' major hub airports. FSCs have also tried to serve more lucrative niche routes that were previously monopolized by Spring Airlines.

This thesis also explores the impacts of the pandemic on MASs worldwide, providing insights into the adaptability of MAS structures during a global crisis. Analyzing airline schedule data for 53 sample MASs, study 2 examines three dimensions of MAS structures before and during the late stages of the pandemic: (i) traffic and degree centrality distribution, (ii) intra-MAS airport competition, and (iii) airline competition intensity. The empirical findings reveal that MAS structures in Europe and the United States remained relatively stable during the pandemic, largely due to earlier lifting of air travel bans and a

return to pre-pandemic levels in domestic and international markets. In contrast, Asia-Pacific MASs experienced significant changes due to restrictive travel bans, resulting in a more balanced intra-MAS airport traffic distribution, intensified competition, and increased airline concentration levels. These insights underscore the resilience and adaptability of aviation systems during global crises and provide valuable lessons for policymakers and industry stakeholders.

Chapter 3 shifts the focus to the economic benefits of air transport, specifically its role in facilitating bilateral service trade. Using China's annual service trade and air connectivity data with 45 partner countries from 2005 to 2018, study 3 develops a reduced-form gravity-type model and employs an instrumental variable (IV) approach to address endogeneity concerns. This study measures country air connectivity through two key metrics: the number of direct route connections and the average seat capacity per route. The findings indicate that (a) increasing the number of direct routes can significantly promote bilateral service export and import trades; (b) the average route-level traffic density has only marginal positive effects; (c) improving air connectivity would enlarge China's overall service trade deficit, because the transport and travel services imports are promoted more than their exports; and (d) the commercial service exports can be stimulated more than the imports, making China achieve a larger commercial service trade surplus by improving bilateral air connectivity. These results highlight the nuanced effects of air connectivity on different service trade sectors and underscore its importance in fostering a post-industrial economy.

Building on these findings, Chapter 3 also investigates the impact of Open Skies Air Services Agreements (OSAs) on bilateral service trade, with a focus on the United States, the most proactive country in signing OSAs. Using US service trade data from 2005 to 2019, study 4 applies a difference-in-differences (DID) regression model and an IV approach to mitigate endogeneity. The analysis demonstrates that OSAs significantly boost transport and travel service exports and imports. However, while OSAs enhance U.S. service imports, their impact on commercial service exports is statistically insignificant. Study 4 also identifies significant lead and lag effects of OSAs on service trade, emphasizing their long-term benefits. These findings underscore the transformative role of liberalized air service agreements in promoting service trade and fostering international economic integration.

Chapter 4 explores the environmental benefits of air transport by examining its impact on manufacturing firm emissions. This chapter studies the causal relationship between air connectivity and manufacturing firm emissions in China by matching firm data with city aviation development data from 2005 to 2013. The study focuses on sulfur dioxide (SO_2) emissions, which have significant adverse health effects on the human respiratory, cardiovascular, and nervous systems and contribute to nonaccidental death. An air connectivity index is constructed to show how well each city is connected to the aviation network. Using instrumental variable methods, study 5 finds that a 1% increase in city air connectivity leads to a 0.1% decrease in SO_2 emissions from manufacturing firms. This reduction is facilitated by a more accessible aviation network and more frequent interactions of business travelers. Specifically, the reduction is driven by technological advancements in the production and emission control processes due to increased firm green production efficiency and increased patent applications of manufacturing firms, and the growth of the scientific research and technical service industry in the city. This study also uses these estimates to quantify the deaths prevented and years of life saved by the improved air quality caused by enhanced air connectivity. Robustness checks confirm that these findings remain consistent when examining alternative pollutants and different sample specifications. These results highlight the potential public health gains achievable by enhancing air connectivity.

This thesis illustrates the crucial role of air transport in fostering economic growth by enhancing service trade and promoting environmental sustainability through the reduction of firm-level emissions. It also examines the operational strategies of airlines and airports during crises. The findings provide valuable insights for policymakers, highlighting the significance of strategic investments in air connectivity, liberalized air service agreements, and sustainable practices. These measures are essential to fully leverage aviation as a tool for economic development and environmental protection.

Publications during PhD study

1. Oum, T. H., **Wu, X.***, & Wang, K. (2024). Impact of air connectivity on bilateral service export and import trade: The case of China. *Transport Policy*, *148*, 219–233.
2. Wang, W., **Wu, X.**, Fu, X., & Wang, K. (2024). Airline competition in Indonesian domestic market-airline-within-airline strategies and impact of the COVID-19 pandemic. *Transport Policy*, *156*, 1–12.
3. Wang, W., Fu, X., Wang, K., Sun, X., Wandelt, S., Wang, J., & **Wu, X.** (2025). Low-cost carrier development under airline-within-airline strategy: Bibliometric analysis and systematic literature review. *Research in Transportation Business & Management*, 101305.
4. **Wu, X.**, Wang, K., Fu, X., Dong, K., Sun, X., & Oum, T. H. (2025). How does COVID-19 pandemic affect airline's route choice and market contact? − Full-service carriers vs. low-cost carriers in China. *Transportation Research Part A: Policy and Practice*, *191*, 104291.
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6. **Wu, X.**, Fu, X., Lei, Z., & Wang, K. (2023). Impact of the COVID-19 Pandemic on Multi-airport Systems Worldwide. *Journal of the Air Transport Research Society*, 1(1), 117–135.
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Working paper:

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CHAPTER 1.

INTRODUCTION

1.1 Research Background

The aviation industry has experienced remarkable growth globally over the past few decades, becoming a vital component of the global economy. According to the International Civil Aviation Organization (ICAO), the total number of passengers carried on scheduled flights rose from 1.7 billion in 2000 to 4.5 billion in 2019. This expansion has been driven by advancements in technology, increased demand for air travel, and the liberalization of air transport markets. International passenger traffic has surged, with millions relying on air transport for business, tourism, and personal connections. The rise of low-cost carriers has further democratized air travel, making it accessible to a broader audience. The industry has also made significant strides in safety, efficiency, and environmental sustainability, as evidenced by the adoption of more fuel-efficient aircraft and initiatives aimed at reducing carbon emissions. However, the aviation sector faces challenges, including geopolitical tensions, economic fluctuations, and the impact of global events such as the COVID-19 pandemic, which temporarily disrupted travel patterns and highlighted industry's vulnerabilities. As the world recovers, the aviation industry continues to play a crucial role in facilitating global connectivity and driving economic growth. Chapter 2 investigates the performance of the aviation system during the COVID-19 pandemic, while Chapters 3 and 4 focus on the benefits of air connectivity from macro and micro perspectives, examining bilateral service trade and firm-level emissions.

Aviation activity serves as a vital link between cities, enabling efficient transportation of goods and people. Air connectivity is crucial for fostering economic growth, job creation, and facilitating global trade (Brueckner, 2003a; Campante & Yanagizawa-Drott, 2018). Recognizing this, countries and cities actively invest in airport construction and expansion, often providing subsidies to encourage airlines to serve new routes. The global aviation landscape has been significantly shaped by the adoption of open skies agreements (OSA), which promote liberalized air transport by allowing airlines to operate freely between signatory countries. These agreements, initiated in the late 20th century, aim to enhance competition, reduce airfares, and increase the availability of flight options for travelers (Squalli, 2014; Oum et al., 2019). By eliminating restrictions on routes, capacities, and pricing, open skies agreements have facilitated the expansion of international air travel, enabling airlines to respond dynamically to market demands. Notably, the United States has been at the forefront of this movement, having signed open skies agreements with over 135 countries by 2023, which has helped to establish a more interconnected global aviation network. This liberalization has not only benefited consumers through lower fares and greater choice but has also stimulated economic growth by enhancing trade and tourism. According to a study conducted by Winston & Yan (2015), the OSAs signed between the US and other countries have generated an annual gain of 4 billion USD for US international travelers. Currently, more than 70 percent of international departures from the US are directed towards Open Skies partner destinations[1].

As economies transition to post-industrial models, there is a growing emphasis on services over traditional manufacturing. Automation and technological advancements have made service sectors such as finance, information technology, healthcare, and education increasingly vital. Service trade allows countries to leverage expertise in these areas, fostering economic growth, employment, and competitiveness (Arnold et al., 2011; El Khoury & Savvides, 2006). According to World Bank statistics, the global service trade value has grown significantly, from \$5.39 trillion in 2005 to \$13.78 trillion in 2022. The trade in services to GDP ratio reached 13.4% globally in 2022, with some countries, including Luxembourg, Malta, Singapore, and Ireland, exceeding 100%. Employment in the service sector has also increased, rising from 43% in 2005 to 50% in 2022, with regions like Luxembourg, Hong Kong, Singapore, Macao, the Netherlands, Malta, and the United Kingdom having over 80% of their workforce in this sector as of 2022. While numerous studies have examined the impact of transport connectivity on merchandise trade (Bensassi et al., 2015), few have explored its effects on service trade, particularly in light of the significant growth in service trade and the increasing number of OSAs. Chapter 3 aims to address this gap by investigating the impact of OSAs and air connectivity on service trade using data from the United States and China.

[1] The data is from https://www.state.gov/.

In addition, the development of a city-level aviation network plays a crucial role in urban growth. A city's aviation connectivity—how well it integrates into domestic and international air networks, including the frequency of flights to major or capital cities—significantly influences its economic and industrial development as well as future resource allocation. A long-standing intellectual tradition suggests that face-to-face social networks are vital for the transmission of knowledge and information, facilitating various forms of knowledge sharing (Al et al., 2016; Storper & Venables, 2004). While numerous studies have explored the relationship between air activity and economic and employment growth, there has been limited investigation into its role in promoting innovation and addressing environmental concerns. One relevant study by Bahar et al. (2023) demonstrated a positive impact of nonstop flights on corporate innovation outcomes. However, the effect of such innovation, driven by air connectivity, on firm emissions remains unexplored. Chapter 4 aims to fill this gap by examining the extent to which improved air connectivity contributes to emission reductions within manufacturing firms.

1.2 Research Objectives

Given the research background and the research gap, the research questions of this thesis are as follows:

Research questions for studies 1 and 2 in Chapter 2:

Study 1:

As the world's second-largest airline market, China was the first country heavily hit by the pandemic. Its continuous international travel restrictions led to a significant reduction in international traffic for major full-service carriers (FSCs) and limited expansion of Spring Airlines into Northeast and Southeast Asia. Airlines are thus forced to concentrate on the domestic market. This inevitably intensifies airline competition, especially between FSCs and Spring Airlines. Based on the context of the Chinese market, study 1 empirically examines the changes in the domestic airline market structure caused by the pandemic, with a focus on airlines' choice of routes. In particular, we hope to distinguish the pandemic's impacts on FSCs and Spring Airlines. Spring Airlines is the dominant LCC in the Chinese domestic market, which is also the largest and independent LCC (Ma et al., 2021; Wang et al., 2018a; Wu et al., 2020).

In addition, study 1 tries to disentangle two possible effects of the pandemic on airline route choice decisions, namely the "attenuating effect" and the "persistent effect". The attenuating effect refers to the action airlines take at the initial stage of the outbreak, where they may exit from many routes. After the pandemic had been well contained inside China, airlines gradually added back their capacity and re-entered many previously served routes. Such a market recovery suggests a decaying impact of the pandemic and is thus defined as an "attenuating effect". On the other hand, the pandemic could have triggered a fundamental change in airline route choice strategy. Such an effect could last for a longer period, even after domestic airline traffic returns to pre-pandemic levels. The airlines' financial conditions have been fundamentally changed, and the international airline market is still tightly controlled even though the pandemic was well controlled domestically. This relatively long-lasting airline strategy adjustment is thus defined as the "persistent effect" in this study. To recognize the airlines' priorities in entering routes involving different endpoint airports, the airline routes are categorized into different types based on the traffic size of the routes' endpoint airports. To conduct the empirical investigation, we propose and estimate a discrete choice model for airlines' route choices. The impacts of the pandemic on FSCs and Spring Airlines are distinguished by estimating a unified airline route choice model. We also examine the change in market contact between FSCs and Spring Airlines caused by the pandemic. Specifically, we classify the routes into "*FSC monopoly*," "*Spring Airlines monopoly,*" and "*Overlap*." A multinomial model is estimated to show the relative change in the composition of these different types of market contact.

Study 2:

Despite extensive research on the impacts of the pandemic on the air transport industry, there has been relatively little investigation into how MASs have been affected. Many questions remain unanswered in this area. First, the pandemic could have affected different airports in the same MAS differently, causing changes in traffic and connectivity distributions among individual airports. Second, inter-airport competition within MASs might have been affected, with market coverage converging (serving more common destinations) or diverging (serving fewer common destinations) during the pandemic. Last, the pandemic could have caused variations in airline competition (including that among airlines providing differentiated services, such as FSCs vs. LCCs) and their dominance among different airports (such as an airport's hub status). Study 2 aims to address these gaps in the literature by examining the impacts of the pandemic on MASs worldwide from three dimensions: (i) the distribution of traffic and degree centrality within MASs, (ii) competition among airports within MASs, and (iii) the intensity of airline competition within MASs.

Research questions for studies 3 and 4 in chapter 3:

Study 3:

While the impact of transport costs and connectivity on merchandise trade flows has been extensively studied, Study 3 empirically examines the effect of bilateral air connectivity on bilateral service trade flows, with a particular focus on China. Although some services are conducted virtually online, a significant portion of service trade relies on on-site professionals. Many service exports and imports require face-to-face communication and/or meetings, as these interactions are essential for exploring potential business and collaborative opportunities. Among various transport modes, air transport is the most convenient for facilitating the movement of people between countries and reducing trade costs. This study measures air connectivity between countries using two key indicators: (1) the number of direct air routes and (2) air traffic density per route (i.e., the average passenger volume per direct route). It analyzes the impact of these two air connectivity indexes on overall service exports and imports, as well as on the three service trade components: commercial, travel, and transport.

A major challenge in identifying causal inference is the endogeneity issue arising from the mutual relationship between air connectivity and bilateral trade. To address this, the study adopts an instrumental variable (IV) approach. The IV is constructed as the average number of foreign cities that have direct flights to China and the number of foreign cities that have direct flights to the service trade partner countries. This approach helps mitigate endogeneity concerns and provides more robust estimates of the causal impact of air connectivity on service trade flows.

Study 4:

Based on the findings of Study 3, Study 4 delves deeper into the impact of Open Skies Agreements (OSAs) on bilateral service trade. OSAs are widely regarded as instruments for liberalizing the international aviation market, enabling airlines to provide more affordable, convenient, and efficient air services to consumers. In Study 4, the United States is selected as the research sample due to its proactive role in negotiating OSAs, having established agreements with over 130 partner countries. Using U.S. bilateral service trade data and OSA records from 2005 to 2019, the study aims to estimate the causal impact of OSAs on service trade flows.

Additionally, the study identifies the lead and lag effects of OSAs. The negotiation process for OSAs often spans several years, during which airlines and airports may anticipate positive market outcomes even before the agreements are formally signed and implemented. This anticipation can result in early manifestations of OSA effects. On the other hand, lag effects may also occur, as service trade involves intricate supply chains and information dissemination. Business stakeholders typically require time to adapt to and fully capitalize on the opportunities created by the signing of OSAs between two countries. By examining these dynamics, the study provides a comprehensive understanding of both the immediate and long-term impacts of OSAs on bilateral service trade.

Research question for study 5 in chapter 4:

The adverse health effects of air pollution have been extensively studied, with research consistently demonstrating a correlation between exposure to polluted air and premature mortality. Manufacturing firms, as major sources of pollutant emissions, play a critical role in controlling air quality. Various countries have implemented policies to regulate emissions from these firms. For instance, the Chinese government introduced the “Dual Control Zones” policy, which designates specific areas for stricter control of sulfur dioxide (SO_2) and acid rain pollution. However, while government policies have been widely studied, there is limited research on the role of non-governmental factors, such as technological advancements, in reducing emissions. Study 5 aims to address this gap by investigating emission reductions in manufacturing firms from the perspective of technological advancements and knowledge sharing fostered by improved air connections to major cities. Study 5 aims to answer the following research questions: (1) What is the causal impact of city air connectivity on emissions from manufacturing firms? (2) What are the mechanisms that drive this impact? (3) What are the health benefits of reduced emissions resulting from enhanced air connectivity?

In Study 5, we first examine the impact of city-level air connectivity—measured as a weighted count of all destinations accessible via nonstop air service—on SO_2 emissions from manufacturing firms in China between 2005 and 2013. Second, we explore the mechanisms behind this impact, specifically whether firms reduce emissions through technological advancements in either the production process or the emission control process. Third, we quantify the health benefits associated with improved air quality resulting from reduced emissions. By addressing these questions, the study provides critical insights into the environmental and health benefits of enhancing air connectivity in China.

1.3 Research Significances

Before estimating the social benefits of aviation, we first examine the resilience of the aviation system by analyzing its performance during global crises, such as the COVID-19 pandemic. Aviation resilience denotes the industry's capacity to deal with, adapt to and recover from systemic shocks. This investigation provides critical insights into how airlines and airports adapt to disruptions, offering a foundation for understanding the broader implications of such events on the aviation industry.

Study 1 focuses on airline route choices during the pandemic and the market dynamics between different types of airlines, specifically FSCs and LCCs. This study provides a unique perspective on airline route entry decisions during the COVID-19 outbreak, with a particular emphasis on comparing the strategies and responses of LCCs and FSCs in China. By identifying the persistent and attenuating effects of the pandemic on routes of varying densities, the study sheds light on how different market segments were impacted. For instance, high-density routes may have experienced a quicker recovery due to sustained demand, while low-density routes might have faced prolonged challenges. This exploration not only enhances our understanding of airline resilience but also offers valuable policy implications. Policymakers can use these findings to design targeted support measures for airlines operating in less resilient markets or to incentivize route restoration in underserved areas. Additionally, the study highlights the importance of flexibility in airline business models, suggesting that LCCs, with their cost-efficient operations, may have been better positioned to adapt to the crisis compared to FSCs.

Study 2 builds on this foundation by further investigating airport performance during the pandemic, with a particular focus on MASs. MAS, which involves multiple airports serving a single metropolitan area, presents a unique case study for understanding traffic distribution, airport competition, and airline competition during a crisis. The study examines how traffic patterns shifted among airports within MAS, as some airports may have been more resilient due to their operational flexibility or dominant market position. It also explores the competitive dynamics between airports and airlines. By analyzing these strategies, the study provides insights into how MAS can enhance their resilience to future disruptions. Findings from studies 1 and 2 are crucial for building a more resilient aviation system capable of withstanding future crises while continuing to deliver social and economic benefits.

Transitioning from resilience to economic impact, Study 3 identifies the causal relationship between air connectivity and bilateral service trade between China and its partner countries. While previous research has primarily examined the effects of air transportation costs and trade barriers on merchandise trade (Micco and Serebrisky, 2006; Endo, 2007; Yamaguchi, 2008; Kern et al., 2021), this study expands the literature by focusing on service trade. Specifically, it investigates how direct flight connections and average seat capacity influence service trade. Improved air connectivity reduces travel time and costs, thereby facilitating face-to-face communication and lowering trade barriers in the service sector. This extension highlights the critical role of air transportation in enhancing service trade, offering new insights into the dynamics of international trade.

While Study 3 highlights the importance of air connectivity in facilitating service trade, Study 4 takes a step further by examining how formal agreements like OSAs amplify these effects. OSAs are bilateral or multilateral agreements designed to liberalize air services between countries by removing restrictions on flight frequency, routes, and pricing. By increasing flight frequency and reducing airfares, OSAs make cross-border travel more affordable and convenient, thereby encouraging face-to-face interactions that are crucial for service sectors such as tourism, education, consulting, and financial services. These sectors often rely heavily on personal interactions, and improved air connectivity directly enhances their growth and international integration. Study 4 provides critical insights into the transformative role of OSAs in enhancing service trade. It demonstrates how policy interventions in air transportation can serve as a powerful tool for economic liberalization, reducing trade barriers, and fostering international cooperation.

Furthermore, in addition to examining air connectivity at the country level, Study 5 also investigates the benefits of city-level air connectivity on firm emission control. Study 5 contributes to the growing body of research focused on controlling emission pollution. Currently, most studies evaluate the direct effects of government environmental regulations. From a market mechanism perspective, scholars have explored the impact of environmental taxes and tradable emission allowances on controlling pollution and fostering environmental innovation (Brunnermeier & Cohen, 2003; Helm, 2003; Lans Bovenberg & de Mooij, 1997). However, there has been limited investigation into the impacts of improved access to more productive or green production markets, which represents an indirect approach to emission control. When a city is well connected to the national innovation network, its firms can benefit from technological advancements in other cities, leading to improved green production efficiency and reduced pollution emissions. This study uses a city's connectivity within the aviation network as a proxy for its connection to the national innovation network and examines the impact of such connectivity on firm green production efficiency, as well as its impacts on firm emissions. Our research fills this gap and provides insights into how improved air connections to major cities or markets can contribute to controlling emissions. We also discuss what types of direct flight connections should be established to maximize knowledge transfer and learning.

1.4 Research Organization

This thesis consists of five chapters, and the structure of this thesis is organized as follows.

Chapter 1 introduces the research background and key questions of the thesis, discussing the development of the global aviation system and the role of air connectivity in service trade and knowledge sharing.

Chapter 2 analyzes the impact of the COVID-19 pandemic on the aviation system, focusing on airline route choices and the performance of multi-airport systems.

Chapter 3 examines the benefits of a well-developed aviation network by investigating the impact of country-level air connections on bilateral service trade using data from China, as well as the effect of open skies agreements on service trade in the US, including the lead and lag effects of these agreements.

Chapter 4 explores the advantages of a well-developed city-level aviation network by investigating the impact of air connectivity on knowledge sharing and its subsequent effect on emissions from manufacturing firms.

Chapter 5 concludes the thesis and offers suggestions for future research.

CHAPTER 2.

THE AVIATION SYSTEM'S RESPONSE TO DISRUPTION: A CASE STUDY OF THE COVID-19 PANDEMIC

CHAPTER 2: PREFACE

In the following chapter, I use empirical models and data analysis to investigate the performance of the aviation system in responding to significant external shocks, such as the outbreak of a pandemic. This chapter will first examine the impact of the COVID-19 pandemic on airlines' route choices and the market interactions between full-service carriers (FSCs) and low-cost carriers (LCCs) in the context of China. Additionally, it will explore the effects of the COVID-19 pandemic on multi-airport systems (MAS) worldwide, including traffic and network size distribution within MAS, intra-MAS airport competition, and market overlap.

The work presented in this chapter has been published verbatim under the titles "How Does the COVID-19 Pandemic Affect Airlines' Route Choices and Market Contact? — Full-Service Carriers vs. Low-Cost Carriers in China" in *Transportation Research Part A: Policy and Practice* (Wu et al., 2024) and "Impact of the COVID-19 Pandemic on Multi-Airport Systems Worldwide" in the *Journal of the Air Transport Research Society* (Wu et al., 2023), with minor edits made to adapt the formatting to match other chapters. In these two studies, I take the lead in developing the empirical model, interpreting the results, and drafting the manuscript, while acknowledging the valuable contributions of my co-authors in providing guidance, and revising the paper. The study in Section 2.1 extends the scope of my master's thesis by incorporating a broader timeframe, employing the instrumental variable method to address endogeneity concerns, and conducting a more rigorous and detailed examination. This chapter synthesizes and expands on these prior works to provide a comprehensive exploration of the topic.

2.1 Impact of the COVID-19 Pandemic on Airline's Route Choice and Market Contact: The Case of China

2.1.1 Abstract

This section empirically examines the impact of the COVID-19 pandemic on airlines' route choices and market contact based on the Chinese domestic market over the period 2019-2022. An airline route choice model is estimated for both full-service carriers (FSCs) and Spring Airlines, China's largest and most representative low-cost carriers (LCCs)[2], which disentangles the "attenuating" and "persistent" effects of the pandemic on airlines' route choices. The former effect refers to airlines exiting from extant routes in response to the sudden decline in air travel demand and strict pandemic controls, while the latter effect reflects airlines' relatively long-term adjustment of their competition strategy triggered by the pandemic. The empirical findings are as follows: The pandemic had a positive "persistent effect" and a negative "attenuating effect" on Spring Airlines. Spring Airlines has actively expanded its network to all types of routes, especially the dense routes connected to major airports. FSCs also adjusted their route entry strategy by entering more thin routes connected to secondary cities (i.e., a positive "persistent effect"). The pandemic has broken the equilibrium of network differentiation between FSCs and Spring Airlines in China. Spring Airlines has begun expanding services at FSCs' major hub airports. FSCs have also tried to serve more lucrative niche routes that were previously monopolized by Spring Airlines. Overall, this study observes more frequent market contact and increasing head-to-head competition between FSCs and Spring Airlines during the pandemic, when the overall traffic volume has rebounded to the pre-pandemic level. This may be attributed to the airlines' desperate need for cash flow amid financial difficulties, forcing them to intensify competition. This could have also been facilitated by more idle aircraft/airport

2 China currently has eight LCCs: Spring Airlines, Chengdu Airlines, China United Airlines, Lucky Air, West Air, Jiuyuan Airlines, Urumqi Air, and Air Guilin. Spring Airlines holds a dominant position as both the LCC leader and the only independent LCC, commanding 40% of the total LCC passenger traffic in 2020. The remaining seven carriers, all subsidiaries of FSCs, each accounted for less than 20% of the market share during the same period.

slot capacities reallocated from the international market to the domestic market during the pandemic.

2.1.2 Introduction

The COVID-19 pandemic (hereafter referred to as "pandemic") has brought unprecedented shocks to the aviation industry (i.e., Zhang et al., 2020a; Czerny et al., 2021; Sun et al., 2020, 2021a b, 2022a b; Oum et al., 2020; Wu et al., 2023). Although major domestic markets have rebounded, the market structure may have changed fundamentally. On the one hand, passengers' travel and ticket booking behaviors may have changed. People have become more adapted to online meetings, hence potentially reducing the need for air travel, particularly for business class passengers (Chen et al., 2022a). Passengers could also have become more price-inelastic because they now fly for essential purposes (Zhang et al., 2021). On the other hand, airlines have also adjusted their competition strategies or network configurations to alleviate financial pressures (Zhang et al., 2022). Due to strict international air travel bans from 2020 to 2022 in most major airline markets around the world, many gateway airports have plenty of slots that were previously used by international flights and are now available for domestic flights (Hou et al., 2021; Mueller, 2022). Airlines also have idle fleets to be deployed from international routes to the domestic market. Therefore, even though air traffic recovers to pre-pandemic levels (December 2019), airlines' domestic route choices and market competition structure may change.

As the world's second-largest airline market, China was the first country heavily hit by the pandemic. Its continuous international travel restrictions led to a significant reduction in international traffic for major full-service carriers (FSCs) and limited the expansion of Spring Airlines into Northeast and Southeast Asia. Airlines are thus forced to concentrate on the domestic market. This inevitably intensifies airline competition, especially between FSCs and Spring Airlines. However, the pandemic might lead to quite heterogeneous impacts on FSCs and Spring Airlines. FSCs, especially the Big Three Airlines (i.e., Air China, China Eastern, and China Southern), have reported huge financial losses in the past two years. According to their financial reports, the Big Three incurred a total loss of RMB 41 billion (about USD 6.3 billion) in 2021[3]. In comparison, Spring

[3] See relevant news report (in Chinese) at

Airlines, the largest LCC in China, earned a positive profit of RMB 39 million (about USD 6.2 million) in 2021[4]. Such different financial performances imply that Spring Airlines might be more flexible in adapting its operations to better deal with the adverse market conditions caused by the pandemic. Intensified market competition could have benefited Spring Airlines at the expense of FSCs. However, it is unclear whether the changes are transitory or permanent. It is important to understand the patterns and mechanisms behind them so that the aviation industry can be better prepared for the market's recovery and sustained growth post-pandemic.

Based on the context of the Chinese market, we empirically examine the changes in the domestic airline market structure caused by the pandemic, with a focus on airlines' choice of routes. In particular, we hope to distinguish the pandemic's impacts on FSCs and Spring Airlines. Spring Airlines is the dominant LCC in the Chinese domestic market, which is also the largest and independent LCC (Ma et al., 2021; Wang et al., 2018a; Wu et al., 2020). Before the pandemic, FSCs dominated dense Chinese routes, especially those involving major hub airports (namely those in Beijing, Shanghai, and Guangzhou). Spring Airlines, however, mainly served routes to the secondary cities (e.g., Lanzhou, Shijiazhuang, Fuyang among others) (Fu et al., 2015a; Liu and Oum, 2018; Su et al., 2020). Although Spring Airlines wants to serve lucrative dense routes connected to major airports, it has been difficult for it to obtain entry permits, as the Civil Aviation Administration of China (CAAC) gives priority to state-owned FSCs. Airports in Beijing, Shanghai, and Guangzhou are the hubs for the Big Three airlines. These airports are constrained in terms of their capacity, which puts Spring Airlines at a disadvantage in trying to obtain scarce slot resources (Fu et al., 2015a). Spring Airlines may have used the "puppy dog" strategy[5] to avoid head-to-head competition or a price war with FSCs by avoiding dense routes (Fu et al., 2015a). Spring Airlines accounts for quite a small market share (less than 20%) and may not be able to sustain fierce competition with FSCs. Due to the pandemic's international flight ban, hub airports had idle slots. CAAC also lessened restrictions on

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https://baijiahao.baidu.com/s?id=1728832513938648147&wfr=spider&for=pc
https://finance.sina.com.cn/chanjing/gsnews/2022-10-31/doc-imqmmthc2742476.shtml

[4]See relevant news report (in Chinese) at https://baijiahao.baidu.com/s?id=1731428783849770056&wfr=spider&for=pc.

[5] Spring Airline offers limited capacity (less than 20% of route capacity) on dense routes to avoid head-to-head competition with full-service airlines.

airlines operating routes out of airports in Beijing, Shanghai, and Guangzhou. Faced with liquidity pressures, Spring Airlines has become more aggressive in entering those dense markets with higher demand and profit potential. Thus, we expect different airline route choice strategies to emerge, which may lead to a significantly changed market structure and competition pattern.

In addition, our study tries to disentangle two possible effects of the pandemic on airline route choice decisions, namely the "attenuating effect" and the "persistent effect". The attenuating effect refers to the action airlines take at the initial stage of the outbreak, where they may exit from many routes. After the pandemic had been well contained inside China, airlines gradually added back their capacity and re-entered many previously served routes (as detailed in Figure 2.1.2). Such a market recovery suggests a decaying impact of the pandemic and is thus defined as an "attenuating effect". On the other hand, as discussed in the earlier paragraph, the pandemic could have triggered a fundamental change in airline route choice strategy. Such an effect could last for a longer period, even after domestic airline traffic returns to pre-pandemic levels. The airlines' financial conditions have been fundamentally changed, and the international airline market is still tightly controlled even though the pandemic was well controlled domestically. This relatively long-lasting airline strategy adjustment is thus defined as the "persistent effect" in this study. Other empirical studies have proposed similar concepts to study the impacts of one particular important event on the transport industry. For example, Ito and Lee (2005) found that the "911 terrorist attack" caused short-term panic among passengers, thus reducing air travel. But this negative effect attenuated quickly over time when passengers regained confidence in airline security. The tightened security measures at airports nevertheless caused a more persistent adverse impact on the US airline industry that lasted for a much longer period. Similarly, Wang et al. (2018b) found that the Yong-wen high-speed rail (HSR) accident, which happened in 2013, only had a very short-term negative effect on HSR passengers' confidence in HSR safety, but the resultant HSR speed reduction ordered by the government resulted in a more persistent traffic shift from HSR to airlines.[6]

[6] Disasters or other exogenous shocks are likely to trigger persistent or permanent changes in the market structure of the transport industry. The Kobe earthquake in 1995 is a good example. Chang (2000) found that the Port of Kobe never recovered to the pre-earthquake level of throughput, although overall shipping demand has been rising rapidly. This is because the short-term shutdown of the Port of Kobe resulted in a permanent

To conduct the empirical investigation, we propose and estimate a discrete choice model for airlines' route choices. The impacts of the pandemic on FSCs and Spring Airlines are distinguished by estimating a unified airline route choice model. The airline routes are categorized into different types based on the traffic size of the routes' endpoint airports. This is to recognize the airlines' priorities in entering routes involving different endpoint airports, which is defined later. We also examine the change in market contact between FSCs and Spring Airlines caused by the pandemic. Specifically, we classify the routes into "*FSC monopoly*," "*Spring Airlines monopoly,*" and "*Overlap*." A multinomial model is estimated to show the relative change in the composition of these different types of market contact.

Our empirical evidence confirms the existence of a clear "attenuating effect" such that airlines quickly re-entered the previously served routes after the pandemic was contained. The pandemic also imposed a strong positive "persistent effect" on the entry of Chinese airlines into various routes (i.e., network expansion) in the domestic market. To summarize, both FSCs and Spring Airlines exited many routes at the beginning of the pandemic, but quickly resumed services after the pandemic was under control. Following more favorable route entry policies introduced by CAAC in September 2020, Chinese airlines have become more active in expanding their domestic networks. Spring Airlines has been more aggressive in entering routes that link with FSCs' hub cities (notably Beijing, Shanghai, Guangzhou, and Chengdu). This suggests an overall intensified competition with increasing head-to-head market contact between Spring Airlines and FSCs in the domestic market. Such aggressive network expansion in the domestic market could be attributed to the airlines' idle fleet capacity and hub airports' unused slots due to the suspension of international services.

The rest of this subchapter is structured as follows. Section 2.1.3 reviews relevant literature. Section 2.1.4 describes data and presents some preliminary summary statistics for straightforward insights. In Section 2.1.4, we specify the econometric model and estimate the "attenuating" and "(relatively) persistent" impacts of the pandemic on the route choice of FSCs and Spring Airlines, respectively. The multinomial model is also

switch of shippers to other rival ports, such as Pusan and Kaohsiung.

specified and estimated to measure the changes in market contact between FSCs and Spring Airlines. The last section summarizes this study.

2.1.3 Literature Review

This study is related to three streams of literature. The first is the impact of the pandemic on the airline market. The second is the competition between Spring Airlines and FSCs in the Chinese market. The third is airline route entry decisions and airline network formation. In the past two years, academic research on the impact of the pandemic on the airline industry has flourished. For example, Sun et al. (2021a) conducted a comprehensive survey on the relevant literature. They suggested that existing studies focus on an analysis of the global air transport system during the pandemic, the impacts on the passenger-centric flight experience, and the long-term impacts on the aviation industry. Using an ITS SARIMA model, Andreana et al. (2021) found that the real effect of COVID-19 on air service volumes was a reduction above 80% in all the world's macro-regions in May 2020, except for China and Eastern Asia, as well as North America, where the reductions were -29% and -54%, respectively. Using global real-time airline flight data, Sun et al. (2020) found that the pandemic damaged the international airline market more than the domestic market, which recovered relatively quickly after the pandemic was brought under control. For example, the Chinese domestic airline market had resumed to almost pre-pandemic traffic levels by the end of 2020 (e.g., Hou et al., 2021; Zhang et al., 2021). However, airlines around the world are faced with great financial difficulties. For example, Dube et al. (2021) found that the pandemic damaged airlines' financial performance significantly, especially that of the major global carriers. This resulted in rating downgrades as well as the liquidation and bankruptcy of many major global airlines. Atems and Yimga (2020) quantified the dynamic responses of US airline stock prices following the outbreak of the pandemic and showed that airline stock prices declined immediately by 0.1 percentage point in response to a 1% increase in confirmed COVID-19 cases. Xuan et al. (2021) forecasted that airline revenues would continue to decline and were expected to return to pre-pandemic levels in 2023. In addition, Iacus et al. (2020) concluded that in the first quarter of 2020 the impact of aviation losses could have negatively reduced world GDP by 0.02% to 0.12%. Czerny et al. (2021) suggested that the impact of the pandemic on air cargo was less severe than on passenger traffic. The air cargo market even benefited from the pandemic, thanks to the dramatic increase in demand for essential medical supplies (e.g., Suk and Kim, 2021; Deng et al., 2022).

The pandemic is also expected to lead to a remarkable change in the travel behavior of airline passengers. Air travelers were more likely to book tickets in a shorter time frame, and cancel flights due to a sudden local outbreak, and there could be a reduction in the number of leisure travelers (see Zhang et al., 2021). The suspension of international flights means idle fleet capacities are available to airlines, and gateway airports have more available slots. In response, airlines are likely to adjust their competition strategies in the domestic market. For example, major Chinese FSCs launched the “Wild Your Weekends” program to offer unlimited travel passes at low prices to attract passengers. Zhang et al. (2022) discovered that this program proved beneficial for airlines in enhancing short-term liquidity. However, it came at the expense of a long-term revenue loss. During the pandemic, governments also introduced a series of favorable policies to support airlines. Abate et al. (2020) suggested most governments gave high priority to maintaining air transport connectivity to protect economic activity and jobs, such that direct financial support was provided to the major airlines. But the trade-off between ensuring connectivity and maintaining competition after the pandemic is a challenge (Rothengatter et al., 2021). Zhang and Zhang (2021) recognized that the government cannot take a hands-off approach in the absence of private lenders and investors to save major airlines. But a minimum level of assistance with conditions might be needed to maintain market competition.

Some studies have tried to identify the heterogeneous impacts of the pandemic on FSCs and LCCs, respectively. Suau-Sanchez et al. (2020) pointed out that, compared to LCCs, the FSCs are more exposed to more distant countries with very different situations and therefore face a more patchy and slower recovery. Ng et al. (2022) investigated the Japanese airline market and found that the pandemic damaged the operation of airlines’ regional routes to a greater extent, and LCCs were more adversely affected, given their preferences for serving regional markets. Jung and Kim (2022) analyzed the productivity changes of six domestic airlines in Korea, including two FSCs and four LCCs, and found that Korean Air, the largest FSC in Korea, experienced improved productivity after the pandemic. The productivity of Asiana Airlines, the second largest FSC, and Air Busan, the largest LCC, has remained unchanged, while the productivity of other smaller LCCs has declined significantly. The improved productivity of Korean Air is due mainly to its booming air cargo business post-pandemic. Korean LCCs placed a much lower emphasis on the cargo sector, which negatively impacted their performance due to the pandemic's negative impacts on passenger traffic. Hyoseok et al. (2021) conducted a similar study on the Korean market and reached the same conclusions. They further suggested that Jeju Air, a smaller LCC in Korea, has seen the most serious productivity downgrading, because of the significant drop in both domestic and international air travel. Warnock et al. (2021) analyzed the Chinese market and found that the FSCs, whose networks focused more on international markets, premium traffic, and discretionary leisure travel, had been most harmed by the pandemic, and were likely to take the longest time to recover. Although these studies offer valuable insights into the impact of the pandemic on the airline market, there are still some limitations and research gaps to be filled. First, the previous literature focuses on the net impact of the pandemic without identifying the mechanism behind it. Therefore, the current empirical results confound the negative impact of the pandemic on airline traffic (especially at the initial stage when the pandemic had not been well controlled) and the airlines' possible adjustments in operation strategies. Some recent efforts have been made to analyze the heterogeneous impacts of the pandemic on productivity and financial performance. There has been little discussion or empirical evidence on airline route choice adjustments and the competition between FSCs and LCCs. This study thus aims to fill these research gaps.

Many scholars have studied the impact factors of airline route entry decisions and airline network formation (Abdelghany and Guzhva, 2010; Aguirregabiria and Ho, 2012, 2012; Bachwich and Wittman, 2017; Bailey et al., 1981; Berry, 1992; Bontemps et al., 2023). Morrison and Winston (1990) conducted one of the earliest studies in this area, analyzing quarterly data from 1979 to 1988 for 13 airlines. They found that an airline's route entry and exit decisions are primarily influenced by its network characteristics rather than those of its competitors. Abdelghany and Guzhva (2010) utilized quarterly panel data covering the largest 10,000 city-pairs in the domestic US to analyze airlines' market entry and exit decisions. Their results indicated a preference for airlines to enter markets with high market concentration and high average fares. Zou and Yu (2020) adopted discrete choice models to examine the factors influencing route entry decisions by Southwest and JetBlue airlines. The results indicated that both airlines are more inclined to enter routes where they possess a higher market share in terms of traffic and connectivity at the endpoint airports. However, they were less likely to enter routes involving endpoint airports with a higher concentration in either traffic or connectivity. Oliveira and Oliveira (2022) investigated the impact of Azul's merger with a regional carrier on its entry decisions using a discrete-choice model. Their findings indicated that following the merger, Azul strategically targeted the regional flight segment to establish monopolies across the country. In their analysis of the UK-Europe airline markets from 1997 to 2004, Gil-Moltó and Piga (2008) assessed the entry and exit activity and examined the distinctive characteristics of three major airlines: British Airways, EasyJet, and RyanAir. Their findings indicated that entry and exit are more likely to occur in larger markets and in markets with a higher number of existing competitors. Overall, these studies contribute valuable insights into the factors influencing airline entry and exit decisions, including network characteristics, market concentration, market share, and strategic considerations. This study aims to offer a perspective on investigating airline route entry decisions specifically during the outbreak of COVID-19, with a focus on comparing the differences between LCCs and FSCs in China.

This study is also related to the research on LCC development and its competition with the FSCs in the Chinese market. Compared with other major airline markets, such as the US, Europe, and Southeast Asia, China still lags significantly behind in LCC development. LCCs make up less than 20% of all domestic airline traffic (Ma et al., 2021). Fu et al. (2015a) estimated the impacts of Spring Airlines on the FSCs' ticket price. They found that FSCs did not significantly lower prices in the presence of the Spring Airlines competition. Spring Airlines, which had a very small market share, adopted "puppy dog" and "cream-skimming" strategies by not offering heavily discounted fares for fear of retaliation by the FSCs. Fu et al. (2015a) also found Spring Airlines preferred to enter thin routes linking secondary cities. The airline had been reluctant to enter or expand capacity on routes involving the major hub airports (Beijing, Shanghai, and Guangzhou). This was due to the CAAC's restriction and protection of state-owned FSCs, and Spring Airlines' intention to avoid a price war it may not be able to sustain. Wang et al. (2017) studied the feasibility of LCC development to help expand the Chinese inter-city transport network to mid- and western China. They concluded that HSR and LCCs provide more substitutable services, such that China's fast HSR network expansion has crowded out LCCs' room for survival. This explains why Spring Airlines has been aggressive in expanding international routes to Northeast and Southeast Asia. Liu and Oum (2018) also suggested the huge potential of LCC development in China, especially following China's liberalization of its airline market by signing open-skies agreements (OSA) with ASEAN and Japan in recent years. A recent paper by Fu et al. (2022) conducted a comprehensive study on the competition between Chinese FSCs and LCCs, focusing on the newly emerged LCCs formed by FSCs (i.e., subsidiary LCCs of FSCs created under the airline-within-airline strategy). Using data up to 2018, they found that before the pandemic, FSCs and LCCs had reached equilibrium in network configurations. FSCs focused more on the dense routes involving the hub airports, while LCCs preferred relatively thin routes. Meanwhile, FSCs used their subsidiary LCCs to explore the lucrative thin routes (i.e., the tourism routes), although mostly limited to niche destinations in Southwest or Northwest China. However, Fu et al. (2022) argued that it is unclear whether the competition between FSCs and LCCs and airlines' route configuration have been reshaped by the pandemic in the long term. This study thus aims to provide answers to these questions with a rigorous and direct empirical investigation.

2.1.4 Data Descriptions

This section first introduces data sources and variable constructions. Some preliminary summary statistics are also presented to shed light on the clear patterns of the pandemic's impacts on airlines' route choices. We collected airline-route-specific data of all Chinese airlines from the IATA PaxIS database, which contains the departure and arrival airports of each route, the operating airline, and airline-specific passenger volume on a monthly basis. Our monthly data covers the period from January 2019 to December 2022. To identify the airline route choices, we rely on the actual airline operation data in the IATA PaxIS database. Although the IATA PaxIS database also reports ticket price data, its accuracy during the pandemic cannot be guaranteed.[7] Therefore, this study does not

[7] Cancellation of ticket bookings was quite frequent compared with the pre-pandemic periods, and the airlines also provided several promotion programs (e.g., passes for unlimited trips). The ticket booking reservation

examine the ticket price or the change in airline demand since the pandemic. In comparison, the airlines' information on route choices is quite reliable, as we know for sure that one flight was operated once it served passenger traffic in a given month.

To examine the impact of the pandemic on airlines' choice of routes, we first classify the sample routes into different categories based on endpoint airport size. Airport passenger traffic volume serves as a commonly used indicator to measure an airport's role within the aviation system. In China, the routes that involve airports with large air passenger volumes are dense and lucrative. The CAAC tightly controls route entry involving major Chinese airports, such as Beijing, Shanghai, and Guangzhou (e.g., Wang et al., 2014; Fu et al., 2015b; Zhang and Zhang, 2016). Figure 2.1.1 exhibits the rank of monthly air passenger traffic in 2019 for Chinese cities. For cities with a multi-airport system (MAS), we aggregated their traffic into the city level.[8] There is a clear hierarchy in air passenger volume among Chinese cities, as exhibited in Figure 2.1.1. The K-means clustering algorithm (Adikariwattage et al., 2012; Cui et al., 2017; Chen et al., 2020) is applied to verify the classification.[9] The first group consists of five cities with the largest air passenger volume, namely Beijing, Shanghai, Guangzhou, Shenzhen, and Chengdu.[10] The second group includes cities with the 6^{th}-9^{th} largest air passenger volume. The third group includes the 10^{th}-23^{rd} cities. The rest of the cities make up the last group. The list of the top 23 cities with the largest airline traffic is shown in Table A1 of the Appendix. As a robustness check, we also tried to classify cities into five groups and six groups, while the main regression results and conclusions remain qualitatively the same.

Airline routes are categorized based on the endpoint cities. We define "*Density1*" routes as those connected with the five cities that have the largest passenger volume in

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system could not fully adjust to such frequent abnormal reservations and changes, leading to poor quality of ticket price data and passenger traffic.

[8] The airline traffic volumes of Shanghai Pudong, and Hongqiao airports are aggregated; the airline traffic volumes of Beijing Capital and Daxing airports are aggregated.

[9] The K-means clustering algorithm is employed to group the data according to their similarities by pre-defined criteria. It is a kind of iterative solution clustering analysis algorithm. The step is to divide the data into k groups, select k objects randomly as the initial clustering center, and then calculate the distance between each object and each seed clustering center. Assign each object to its nearest cluster center. Cluster centers and the objects assigned to them represent a cluster. For each sample assigned, the cluster center of the cluster is recalculated based on the existing objects in the cluster. This process is repeated until some termination condition is met.

[10] Beijing is the hub for Air China; Shanghai is the hub for China Eastern; Guangzhou is the hub for China Southern; Chengdu is the hub for China Southern; Shenzhen is the hub for Air China.

China; "*Density2"* routes are those connecting the 6th-9th cities with other cities having less air passenger volume; and "*Density3"* routes are those connecting the 10th-23rd cities to other cities with less air passenger volume. Those remaining routes are categorized as "*Others"*. We classify Chinese routes according to the endpoint city's air passenger volume for the following reasons. First, Chinese domestic traffic is concentrated mainly on routes linking the major hub airports. The hub airports in Beijing, Shanghai, and Guangzhou contribute most of the domestic network connectivity. Secondary cities prefer to expand air connectivity first with the major hub airports, especially Beijing, Shanghai, and Guangzhou (e.g., Gong et al., 2018; Deng et al., 2022). Second, the entry into those routes involving the major Chinese airports has been tightly controlled by the CAAC, not only to protect the incumbent FSCs, but also due to scarce slot resources (see Fu et al., 2015b, 2020; Tan et al., 2021). All the endpoint airports used to define *Density1* and *Density2* routes are "IATA Level 3 Slot Coordinated Airports."

As a robustness check, we also tried alternative approaches to divide routes. The top three cities (Beijing, Shanghai, and Guangzhou) appear to be more distinct. These three cities are the international gateways in China, and are the main hubs of the Big Three airlines. Thus, we also tried to re-define the *Density1* routes as those involving only the top three cities. *Density2* routes are also adjusted, connecting the 4th-10th cities to those with smaller traffic volumes. In addition, a more straightforward approach is to divide the routes based on route-level passenger volume. We also implemented the *K-means* clustering on route-level passenger volume, and estimated the econometric models based on such route categories. All our major conclusions prove to be very robust and do not change qualitatively. All our robustness estimation results have also been collated in Appendix A.

As a preliminary check, Figure 2.1.2 shows the number of routes during the pandemic in the Chinese domestic market, which includes all LCCs and FSCs. To better compare the changes in route service before and during the pandemic, we have standardized the values for December 2019 as 1. With Wuhan being locked down in late January 2020, China restricted the city's inter-city traffic, with most of the population quarantined at home in February and March 2020 (e.g., Huang et al., 2020; Zhang et al., 2020b). Countrywide, all airlines were forced to suspend services on most of their routes and cut capacity to reduce operating costs. This is clearly shown by the dramatic drop in the number of routes from

February to April 2020. With the pandemic well contained domestically, the airlines gradually added back capacity and resumed services, leading to an increasing number of routes since May 2020. Such a pattern suggests the pandemic's negative impact has been attenuating over time. Figure 2.1.3 distinguishes the patterns by FSCs and Spring Airlines. Compared with FSCs, Spring Airlines exhibits a faster speed of recovery. This seems to suggest that Spring Airlines is more resilient and flexible in adjusting its network configuration.

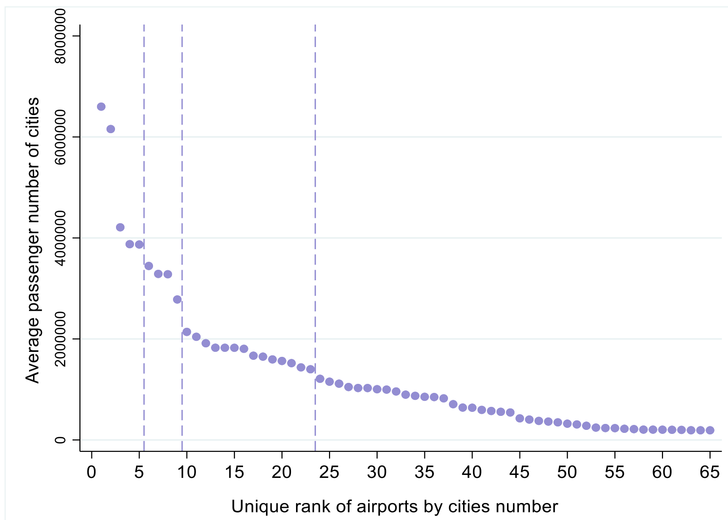


Fig. 2.1.1: Monthly average passenger volume of Chinese cities during 2019

Notes:

1. The vertical purple lines divide the cities into different categories.
2. To save space, we only plot the top 65 cities.

Data source: Compiled by the author based on IATA PaxIS data (same for the Figures 2.1.1-2.1.4).

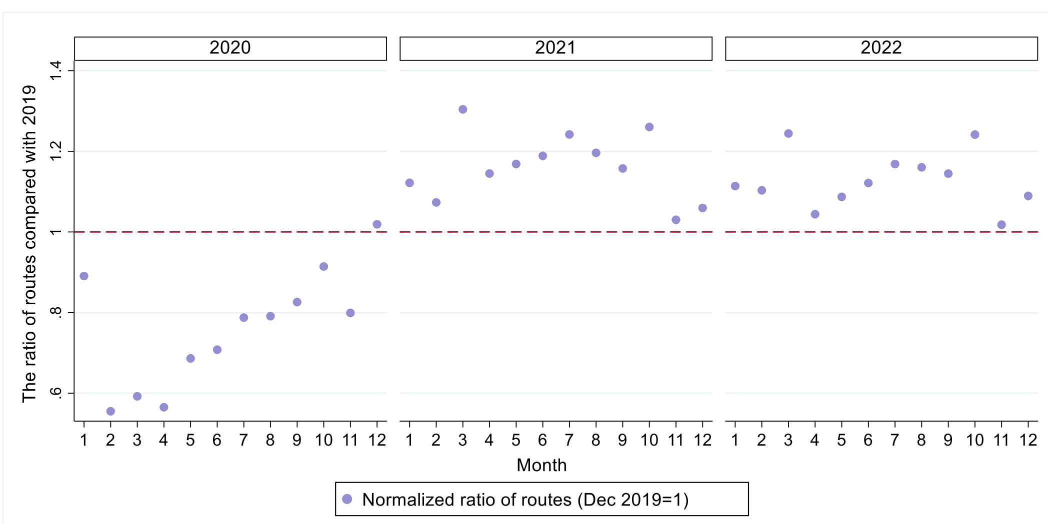


Fig. 2.1.2: Normalized ratio of routes compared to 2019 (Jan 2020 to Dec 2022)

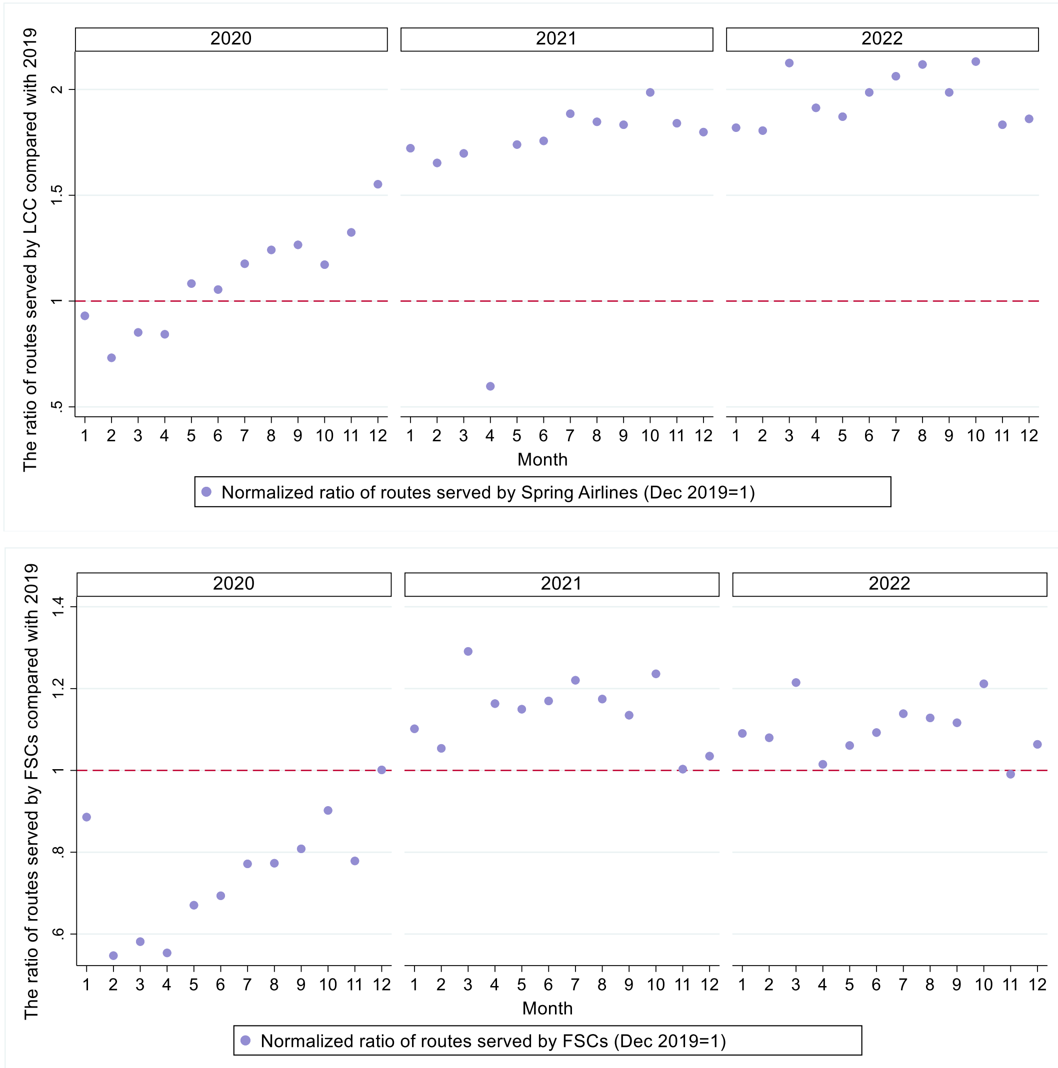


Fig. 2.1.3: Normalized ratio of routes served by Spring Airlines and FSCs compared to 2019 (January 2020 to December 2022)

Notes:

1. The upper panel is for Spring Airlines, and the lower panel is for FSCs.
2. We excluded the data in April 2021 in our regression analysis due to outliers from Spring Airlines. Upon reviewing the monthly report from Spring Airlines, we did not observe significant differences in operational data between April and March 2021.

Next, we examine the patterns of different kinds of routes. The top Chinese airports had more international traffic before the pandemic. Thus, they also had more available slots to be reallocated to domestic flights after the outbreak of the pandemic. In September 2020, CAAC formally announced to relax the access restrictions for feeder routes involving the three major airports in Beijing, Shanghai, and Guangzhou[11]. Previously, airlines applied

[11] See relevant news report (in Chinese) at http://www.caac.gov.cn/XWZX/MHYW/202009/t20200916_204552.html

for feeder routes with an annual passenger throughput of less than 2 million to the three major airports needed to meet the additional requirement of "having at least 15 destinations served in Beijing, Shanghai, or Guangzhou." To support airlines in exploring potential markets and improving hub networks, and to facilitate the market recovery of medium and small airports, the passenger throughput threshold of 2 million has been lowered to 1 million. This means that 32 airports with passenger throughput between 1 million and 2 million in 2019 can have direct route connections to Beijing, Shanghai, or Guangzhou without being restricted by the number of destinations served. Moreover, in August 2021, the CAAC released the new "Domestic Airline Route Flight Review Rules for China's Civil Aviation."[12] These rules continue the access policy for feeder routes that was implemented in 2020. The CAAC eased restrictions on route entry for airlines into these large airports, especially those in Beijing, Shanghai, and Guangzhou. The pandemic thus offers valuable opportunities for airlines, especially Spring Airlines, to explore lucrative trunk routes linked to the major Chinese airports. As Spring Airlines experienced difficult financial conditions after the outbreak of the pandemic, they may now change their previously adopted puppy dog strategy to aggressively expand services in the major airports, even at major FSCs' hub airports. On the other hand, FSCs dominated the trunk routes linking with their hub airports at Beijing, Shanghai, and Guangzhou. These routes are essential for the FSCs' profitability and network resilience, which are of high priority for the resumption of services. As a result, it is possible that both FSCs and Spring Airlines would compete more aggressively on these dense routes.

As shown in Figure 2.1.4 of the *Density 1* routes, the pandemic forced FSCs to exit these dense routes to a greater extent than Spring Airlines. This is mainly because FSCs have much more capacity than Spring Airlines, especially on these dense routes. In response to the huge drop in demand right after the outbreak of the pandemic, FSCs were more adversely affected. Spring Airlines served fewer dense routes and thus was less affected. It is more interesting to observe that, following the outbreak of the pandemic, Spring Airlines has almost tripled the number of dense routes it serves compared to pre-pandemic levels. The head-on-head competition between FSCs and Spring Airlines is thus

[12] See relevant news report (in Chinese) at http://www.caac.gov.cn/XXGK/XXGK/ZCJD/202108/t20210827_209019.html

expected to intensify.

The above descriptive statistics and discussions help us obtain an overall picture of the route choices before and during the late stage of the pandemic. But the observed patterns could be confounded by many factors that are specific to the routes, airlines, endpoint airports, etc. Thus, in Section 2.1.5, we use econometric estimation to conduct more rigorous empirical investigations.

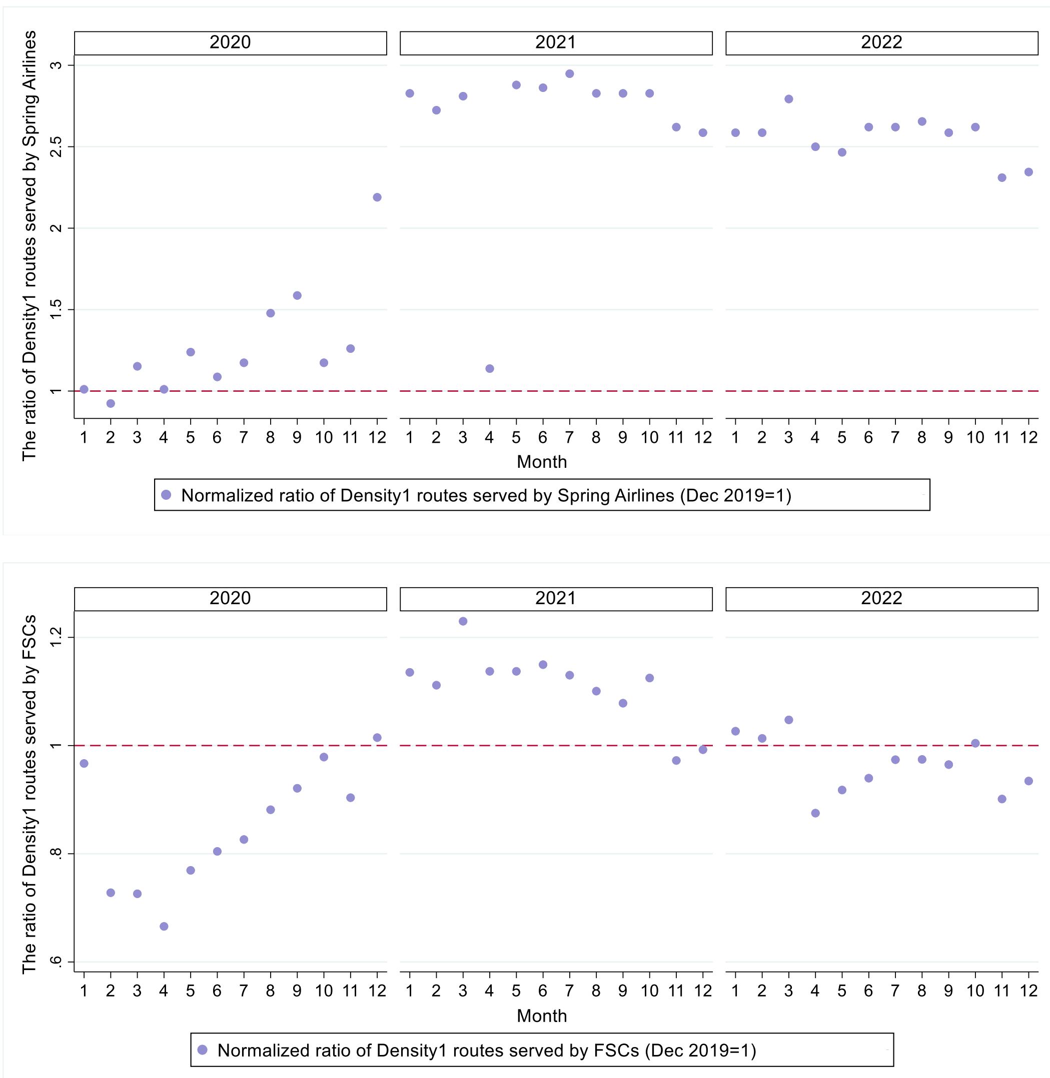


Fig. 2.1.4: The ratio of *Density1* routes served by Spring Airlines and FSCs[13] (January 2020 to December 2022)
Note: The upper panel is for Spring Airlines, and the lower panel is for FSCs.

[13] The ratio of Density1 routes served by FSCs is extremely low in April 2022 due to the lockdown of Shanghai in April.

2.1.5 Econometric Model and Estimations

The summary statistics in Section 2.1.4 offer useful insights on the potential impact of the pandemic on airline route choice in the Chinese domestic market. In this section, we conduct formal econometric investigations. First, a discrete choice model is proposed to estimate the airline's choice of route. This helps identify both the attenuating and persistent effects of the pandemic on the route choice of both FSCs and Spring Airlines. The estimation results are presented and discussed in subsection 2.1.5.1. Given the different route choice strategies adopted by FSCs and Spring Airlines after the outbreak of the pandemic, the competition situation between them could also have been altered. Thus, in subsection 2.1.5.2, we further estimate a multinomial model to measure the impact of the pandemic on market contact between FSCs and Spring Airlines. Robustness checks are shown in subsection 2.1.5.3.

2.1.5.1 Discrete choice model of route choice

The airline's route entry and exit decisions could be complex, which is affected not only by its own operational characteristics but also by the competitors' strategic route choices. A structural model can be used as a sophisticated approach to well account for the airlines' strategic interactions by deriving the econometric estimation models from the airline's competition equilibrium (e.g., Berry, 1992; Bontemps and Sampaio, 2020; Aguirregabiria and Ho, 2012; Bontemps et al., 2022). On the other hand, some studies adopted a latent airline route-level profit function that depends on the route characteristics and the airlines' operational characteristics to derive a reduced-form discrete choice model to depict the airline's route service decisions. The competition effect is incorporated through adding route-level concentration index or rivalry airlines' presence dummies (e.g., Boguslaski et al., 2004; Oliveira, 2008; Homsombat et al., 2014; Fu et al., 2015a; Wang et al., 2020a). The endogeneity issue resulting from competition variables will be discussed later.

For this empirical study, the reduced-form discrete choice model is chosen in the spirit of Boguslaski et al. (2004), Oliveira (2008), Homsombat et al. (2014), Fu et al. (2015a), Wang et al. (2020a). First, the pandemic could have caused significant changes on airlines' demand and cost functions. The airline competition behaviors could also be considerably reshaped. Thus, it may not be straightforward to specify the pandemic's impact on different airlines' cost functions and their competition behaviors. Second, this study is concerned about the dynamic change of route choice evolution during the pandemic. It is technically difficult to derive the dynamic structural model for this problem. The reduced-form model may not well capture the airlines' strategical interactions, but it can provide the overall pandemic impact (also over time) on airlines' route service decisions. The findings are still useful to describe the airline market variations during the pandemic and offer useful policy and managerial implications.

Specifically, an airline's decision to serve a route depends on the profit generated. Although not observed by researchers, an airline's latent profit function π^* by serving one route, can be specified as Eq. (2.1.1).

$$\pi^* = f(\boldsymbol{X}, \beta) + \mu \tag{2.1.1}$$

The airline's latent profit π^* is a function of a vector of observable determinant variables $\boldsymbol{X}$, representing the market and airline characteristics. A stochastic error term μ is also added.

Researchers cannot observe the latent profit π^*, but know the airline's route service decision. Let airlines' entry decision be Y.The entry decision can be specified as a function of the latent profit, such that $Y = 1$ if $\pi^* > C$, and $Y = 0$ if $\pi^* \leq C$. C is the fixed cost for airline to enter a new route. Thus, the probability of route entry can be expressed as Eq. (2.1.2).

$$\text{Prob}(Y = 1|\boldsymbol{X}) = \text{Prob}\left(\frac{\pi^*}{C} > 1\middle|\boldsymbol{X}\right) = \text{Prob}(\ln\pi^* - \ln C > 0|\boldsymbol{X}) \tag{2.1.2}$$

The linear probability model is employed to address the large number of observations and potential endogeneity issue, as the airline's route entry and exit decisions are influenced by both its own operational characteristics and competitors' strategic route choices.

By specifying the determinant variables, the latent profit function can be written as Eq. (2.1.3), with the subscripts i standing for the route, j for the airline, t for the time (each t represents a certain month of a certain year), and *d* for the departure city and arrival city.

$$\ln\pi_{ijt}^* = \varphi_0 + \ln\boldsymbol{X_{ijt}}\,\boldsymbol{\rho} + c_t + \eta_j + \kappa_d + \zeta_i + \mu_{ijt} \tag{2.1.3}$$

In order to accurately decompose the time-varying impact of the pandemic, we initially conducted a very simple regression analysis (Equation 2.1.3) to identify the time trend[14]. Figure A1 displays the estimated sequence of c_t along with their corresponding 95% individual confidence intervals. As shown by the pattern of Density1 routes (Figure A1(a) and (b)), there is a clear trend of recovery that is increasing during the pandemic. In addition to the recovery observed in 2020, the time trend for the year 2021 (time points 25-36) has surpassed the levels seen in 2019, indicating a persistent impact of the pandemic on the airline industry. This finding is consistent with the information presented in Figure 2.1.4. It suggests that airlines have adjusted their route entry strategies in response to the ongoing effects of the pandemic. Furthermore, the figures also illustrate distinct recovery patterns among Density1, Density2, Density3, and Others. And within the same density category, Spring Airlines and FSCs exhibit significant differences in their recovery patterns. Following these observations and the paper by Ito and Lee (2005), we decided to decompose the impact of the pandemic into two distinct components. The first component represents the persistent impact, which captures the long-term strategic adjustments made by airlines. The second component is the attenuating impact, which reflects the initial shock experienced by airlines and how it diminishes over time. We also added the interaction term of the LCC dummy variable and these two pandemic impacts to capture the difference between Spring Airlines and FSCs. The updated latent profit function is shown in Eq. (2.1.4).

[14] Although this semi-parametric approach is very useful for us to identify the possible time trend of the pandemic impact and confirm the existence of the persistent and attenuating effects, it could be subject to limitations. Using a simple regression model, the approach assumes a linear relationship between time and the impact of the pandemic, potentially oversimplifying the actual dynamic and nonlinear nature of the pandemic's effects. In addition, the analysis may not fully account for confounding variables or external factors that could influence the observed recovery trends, leading to potential biases in the estimation of the pandemic's impact. Therefore, this study still develops the regression analysis that considers both linear and decreasing quadratic effects of the pandemic, includes more control variables, and also adopts IVs to deal with the potential endogeneity issues.

$$
\begin{aligned}
\ln\pi_{ijt}^{*} = {} & \varphi_0 + \ln\boldsymbol{X_{ijt}\rho} + \varphi_2 COVID19_t + \varphi_3 \frac{1}{COVID19_{t_t}} \\
& + \sum_{r=1} \beta_r\, Density_{ir} \times LCC_j + \sum_{r=1} \gamma_r Density_{ir} \times COVID19_t \\
& + \varphi_4 COVID19_t \times LCC_j \\
& + \sum_{r=1} \delta_r Density_{ir} \times LCC_j \times COVID19_t \\
& + \sum_{r=1} \theta_r Density_{ir} \times \frac{1}{COVID19_{t_t}} + \varphi_5 \frac{1}{COVID19_{t_t}} \times LCC_j \\
& + \sum_{r=1} \tau_r Density_{ir} \times LCC_j \times \frac{1}{COVID19_{t_t}} \\
& + \eta_j + \kappa_d + \zeta_i + \mu_{ijt}
\end{aligned}
\qquad (2.1.4)
$$

where,

- π_{ijt}^{*}: latent profit of airline *j* for serving route *i* at time *t*;
- LCC_j: dummy variable to indicate whether airline *j* is Spring Airlines;
- $COVID19_t$: dummy variable equals 1 if time t is after January 2020;
- $\frac{1}{COVID19_{t_t}}$: the reciprocal of the number of months post pandemic;
- $Density_{1i}$: dummy variable equals 1 for routes involving the top five cities with the largest air passenger volume;
- $Density_{2i}$: equals 1 for routes involving cities ranked 6^{th}-9^{th} in terms of air passenger volume, with other cities having fewer air passengers;
- $Density_{3i}$: equals 1 for routes involving cities ranked10^{th}-23^{rd} in terms of air passenger volume, with other cities having fewer air passengers;
- $AirportVol_{it}$: product of OD airports' passenger traffic on route *i* at time *t*;
- $RouteHHI_{it}$: HHI index for route *i* at time *t*;
- $AirportHHI_{it}$: HHI index for endpoint airports of route *i* at time *t*;
- $OwnHub_{ij}$: dummy variable equals 1 if one of the OD cities on route *i* is the airline j's hub airport;
- κ_d: the departure city and arrival city fixed effects;
- ζ_i: the route fixed effect;
- η_j : the airline fixed effect;
- μ_{ijt}: a pure random variable representing white noise.

$COVID19_t$ is a dummy variable that equals one if the time is after January 2020. Since China imposed very strict travel bans from February to April 2020, the airlines were forced to suspend most of their domestic services. The operation decisions were largely out of the control of the airlines themselves. Thus, we also exclude the data during this period from the estimation. The dummy variable $COVID19_t$ is used to capture the "persistent effect" of the pandemic on airlines' route choice in that its effect is assumed to be constant during the post-pandemic periods (all the observations after the outbreak of the pandemic in January 2020 have the value of this variable as 1). $\frac{1}{COVID19t_t}$ is the reciprocal of the length of time (in months) after the outbreak of the pandemic. It is used to measure the "attenuating effect" of the pandemic, as the value of this variable decays with the length of the period post outbreak. As airline traffic recovered and air travel restrictions eased over time after the initial outbreak in early 2020, the negative impact of the pandemic decayed over time. This variable's function form is in the spirit of Ito and Lee (2005) and Wang et al. (2018b). We use these two variables to identify the "persistent effect" and "attenuating effect" of the pandemic specifically. It is hard to capture these two effects precisely, so that our imposed functional forms only help capture the overall/mean effects during the study time period. As a robustness check, we also tested the alternative variable forms to measure the attenuating effect, namely $\frac{1}{(COVID19t_t)^2}$ and $\frac{1}{\sqrt{COVID19t_t}}$. The results and discussions are available in Appendix C.

The set of dummy variables $Density_{ir}$ is used to distinguish the airlines' likelihood of serving different types of routes before and during the outbreak of the pandemic. These variables, $Density_{ir}$ have already been specified and discussed in Section 2.1.4. We define *Density1* routes as those that are connected with the top five cities with the largest passenger volume as of 2019. *Density 2* routes are those linking the 6th-9th cities with other smaller ones. *Density3* routes are those linking the 10th-23rd cities with those having less airline traffic. Those remaining very thin routes are categorized as *Others*. As explained in Section 2.1.4, the air passenger volume of the endpoint airports is used, instead of the route-specific traffic, to define the route types, because the route entry permit in China is controlled by the CAAC, especially for routes linking the major airports. In addition, those endpoint airports that previously served more international flights could also have more available slots to be redeployed in the domestic market, which could affect the airlines' route entry decisions. As a robustness check, we have also tried to divide the route types based on the route-level air passenger volume. The corresponding estimation results have been collated in Table A4(a) and Table A4(b) of the Appendix and will be discussed in detail in Appendix C.

To measure the impact of the pandemic on the airlines' route choice for different route types, we include a set of interaction terms in the discrete choice model, i.e., $\sum_{r=1} \gamma_r Density_{ir} \times COVID19_t$, $\sum_{r=1} \theta_r Density_{ir} \times \frac{1}{COVID19_{t_t}}$. Moreover, to distinguish the impacts of the pandemic on FSCs and Spring Airlines, the dummy variable LCC_j (1 for Spring Airlines and 0 for the others) and a set of interaction terms between LCC_j and the density and pandemic variables are also included. To fully examine Spring Airlines' distinct attenuating and persistent pandemic effects on different types of routes, both two-way and three-way interaction terms are further added, i.e., $\sum_{r=1} \beta_r\, Density_{ir} \times LCC_j$, $\varphi_4 COVID19_t \times LCC_j$, $\varphi_5 \frac{1}{COVID19_{t_t}} \times LCC_j$, $\sum_{r=1} \delta_r Density_{ir} \times LCC_j \times COVID19_t$, $\sum_{r=1} \tau_r Density_{ir} \times LCC_j \times \frac{1}{COVID19_{t_t}}$.

These interaction terms help quantify the distinct impacts of the pandemic on Spring Airlines and FSCs and on the different types of routes. Alternatively, one can run the discrete choice models for each subsample of FSCs and Spring Airlines on different types of routes. However, the coefficients from these different model estimations cannot be directly compared with formal statistical inferences. An integrated model with interaction terms allows direct statistical inferences of various effects and offers sufficient flexibility of the model specification (e.g., Choi et al., 2020). For readers' easier reference, Table 2.1.1 summarizes and explains the meaning of coefficient combinations to infer the distinct impacts of the pandemic. The coefficient is calculated by taking the difference between the pandemic and pre-pandemic values, as outlined in Equation 2.1.4, for different airlines serving various route categories (LCC/FSC and Density 1/2/3, Others).

Following previous studies on airline route choice, travel demand, and pricing, we also control other commonly adopted variables. For example, the flying distance $Dist_i$ is commonly included to control for cost and price factors related to the length of the flight stage (Dresner et al., 1996). However, the coefficient for this variable is omitted due to the route fixed effect. $AirportVol_{it}$ controls for endpoint airport sizes on one route. It is equal to the product of endpoint airports' monthly passenger traffic. This serves as a proxy for the potential market demand on one route (Homsombat et al., 2014; Wang et al., 2017). $RouteHHI_{it}$ is used to measure the airline market concentration on the route level (e.g., Wang et al., 2018b). $OwnHub_{ij}$ measures the presence of a hub airport of the airline at the endpoint of one route. Airlines may gain some advantage by serving routes out of their base airport (Borenstein, 1989; Yuen et al., 2017). We also control the airline concentration at the endpoint airports indicated by the variable $AirportHHI_{it}$ to measure the degree of airline competition at the endpoint airport level. Lastly, airlines effects and route effects are also controlled for time-invariant airline- and route-specific unobservable factors. The endpoint cities fixed effect has been incorporated to exclude city relevant unobservable impacts. It should be noted that we also control several local outbreaks over our study period. For example, Beijing and Urumqi experienced a short outbreak in June 2020 and July 2020, as well as Shanghai in April 2022. The endpoint city-time dummies ($Local\ outbreak_{dt}$) are included to control local outbreaks.

The airline market recovery is a dynamic and complex process, with the airline price, traffic, and load factor evolving as well. As a result, the airline profit would change, which directly determines the airline route choice. What we care about is the airline's route service decision, which depends on the equilibrium profit, not the airline price, traffic, or load factor. Therefore, only exogenous variables are included in the equation, which resembles the "reduced-form" estimation.

However, the airline's route entry and exit decisions are influenced not only by its own operational characteristics but also by competitors' strategic route choices. Consequently, competition factors such as $RouteHHI$ and $AirportHHI$ are endogenous, as they are affected by the airline's route entry decisions and, in turn, influence those decisions. This violates the assumption of $cov(X, \mu) = 0$, leading to inconsistent estimates. To address the endogeneity issue, we employ instrumental variable methods, following the approach outlined in Borenstein (1989), and Borenstein and Rose (1994) to construct instrumental variable (IV). The IVs we used are $GMEANPOP$ and IV_Route_HHI, which have been used by other scholars in similar contexts (Dai et al., 2014; Gaggero and Piga, 2010). $GMEANPOP$ is the geometric mean of the populations of the endpoint cities of the route. $IV_{RouteHHI}$ is calculated as Equation (2.1.6).

$$\mathrm{GMEANPOP}_{it} = \sqrt{\mathrm{POP}_{1t} * \mathrm{POP}_{2t}} \tag{2.1.5}$$

where POP_{1t}, POP_{2t} are populations of the origin and destination cities of the route i.

$$IV_{RouteHHI} = \widehat{RouteShare}^2 + (RouteHHI - RouteShare^2) * \frac{\left(1-\widehat{RouteShare}\right)^2}{(1-RouteShare)^2} \tag{2.1.6}$$

Here, $RouteShare$ is the airline's passenger share on the route. $\widehat{RouteShare}$ is the fitted value from its first stage (Equation (2.1.7)).

$$RouteShare_{ijt} = \varpi + \varrho \times \ GeoShare_{ijt} \ + \boldsymbol{G}'\boldsymbol{X}_{ijt} + \upsilon_i + \psi_j + o_d + \varepsilon_{jit} \tag{2.1.7}$$

$GeoShare$ is calculated as Equation (2.1.8). The first stage regression of $RouteShare$ also includes the population of endpoint cities, the route distance, route passenger number, and other control variables in the model.

$$GeoShare \ = \frac{\sqrt{CarrierVolume_{x1} * CarrierVolume_{x2}}}{\sum_y \sqrt{CarrierVolume_{y1} * CarrierVolume_{y2}}} \tag{2.1.8}$$

where y indexes all airlines, x is the observed airline, and $CarrierVolume_{y1}$ and $CarrierVolume_{y2}$ are airline y's monthly passenger number at the two endpoint cities 1 and 2.

$GMEANPOP$ is a valid instrument variable because airlines' route entry decisions would not have a significant impact on the endpoint city's population, while the population could suggest the potential market size to determine the number of serving airlines (route and airport concentration degree), thereby ensuring exogeneity and relevance. $IV_{Route_{HHI}}$ is a valid IV under the assumptions (a) that $GeoShare$ is a valid instrument for identifying airline's $RouteShare$, and (b) that the concentration of traffic on a route that is not carried by the observed airline is exogenous with respect to the entry decision of the observed airline. For example, the fitted route share of Spring Airlines on the route Shanghai-Hengyang is not affected by the Spring Airlines' route entry decision. The entry decision of Spring Airlines on the Shanghai-Hengyang route does not affect how the passengers it doesn't get are divided between Shanghai Airlines and Juneyao Airlines. Under these two assumptions, the IV for $RouteHHI$ is the square of the fitted value $RouteShare$ (from its first-stage regression) plus the "rescaled" sum of the squares of all other airlines' shares. The resealing assures that a HHI index calculated only for passengers who do not travel on the observed airline is unchanged.

We employ a two-stage least squares (2SLS) approach to estimate the linear probability model, where the first stage involves regressing the endogenous variables $RouteHHI$ and $AirportHHI$ on the instrumental variables, and the second stage involves regressing the outcome variable Y on the fitted values of the endogenous variables and other variables in Eq. (2.1.4).

Our data for this model estimation has been introduced in Section 2.1.4 and has been compiled mostly from the IATA PaxIS database. The population data are sourced from the China City Statistical Yearbook. The study time period is January 2019 to December 2022. The descriptive statistics for our sample are reported in Table 2.1.2.

Table 2.1.1 Calculations of the pandemic effects

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	$\varphi_2+\varphi_4+\gamma_1+\delta_1$	$\varphi_3+\theta_1+\varphi_5+\tau_1$
	Density2	$\varphi_2+\varphi_4+\gamma_2+\delta_2$	$\varphi_3+\theta_2+\varphi_5+\tau_2$
	Density3	$\varphi_2+\varphi_4+\gamma_3+\delta_3$	$\varphi_3+\theta_3+\varphi_5+\tau_3$
	Others	$\varphi_2+\varphi_4$	$\varphi_3+\varphi_5$
The effect of the pandemic on FSCs route choice	Density1	$\varphi_2+\gamma_1$	$\varphi_3+\theta_1$
	Density2	$\varphi_2+\gamma_2$	$\varphi_3+\theta_2$
	Density3	$\varphi_2+\gamma_3$	$\varphi_3+\theta_3$
	Others	φ_2	φ_3
The different effects of the pandemic on Spring Airlines vs. FSCs	Density1	$\varphi_4+\delta_1$	$\varphi_5+\tau_1$
	Density2	$\varphi_4+\delta_2$	$\varphi_5+\tau_2$
	Density3	$\varphi_4+\delta_3$	$\varphi_5+\tau_3$
	Others	φ_4	φ_5

Notes: The persistent effect captures the long-term strategic adjustments made by airlines, remaining unchanged during the pandemic. The attenuating effect reflects the initial shock experienced by airlines and diminishes over time.

Table 2.1.2 Descriptive statistics for the variables

Variable	Mean	Std. Dev.	Unit
Airport HHI	0.183	0.085	Unit
Airport Volume[15]	470	1000	Billion people
Route HHI	0.796	0.289	Unit
Distance	605	295	Nautical mile
Own Hub	0.03	0.17	Dummy
LCC	0.028	0.165	Dummy
COVID-19	0.731	0.443	Dummy
1/COVID-19_time	0.052	0.054	1/Month
Density1	0.208	0.406	Dummy
Density2	0.156	0.363	Dummy
Density3	0.282	0.45	Dummy
IV Route HHI	0.794	0.287	Unit
GMEANPOP	841.186	690.149	Ten thousand people
No. of Obs.	8.36 million		Unit

2.1.5.2 Estimation results and discussion

The results of the first-stage regression are reported in Table A2, which shows that the instrumental variables have a significant impact on the endogenous variables. The complete coefficient estimation results for the linear probability model are shown in Table 2.1.3. To focus on the impacts of the pandemic on airlines' route choice, the estimation results have been further organized, as shown in Table 2.1.4, corresponding to the theoretical values reported in Table 2.1.1. We distinguish the pandemic's persistent and attenuating effects, respectively. Table 2.1.4 also distinguishes the impacts of the pandemic on FSCs and Spring Airlines on different types of routes. The net effect is the aggregation of the two effects, with the attenuating effects proportional to the reciprocal of the length of time post pandemic.

Table 2.1.3 also provides some interesting insights from the coefficients of the control variables. The significantly negative coefficient of $RouteHHI$ suggests that airlines are more likely to serve routes with intense competition, which may be due to the fact that high-traffic and high-profit routes tend to be more competitive. However, the coefficient of $AirportHHI$ is not significant, indicating that airlines are not influenced by the

[15] The airport volume for a route is measured by the product of the airport passenger volumes of the two endpoints, such that the unit of this variable is huge.

competitive situation at the endpoint airports when making entry decisions. The significantly positive coefficient of $AirportVolume$ reveals that airlines prefer to enter routes connected to airports with high passenger throughput. The significantly positive coefficient of $OwnHub$ suggests that airlines tend to expand their network from their hubs when entering new routes.

Table 2.1.3 Estimation results of the linear probability model (IV)

VARIABLES	Coefficients	VARIABLES	Coefficients
lnRoute_HHI	-0.054***	Density2COVID_19	-0.015***
	(0.001)		(0.001)
lnAirport_HHI	-0.017	Density3COVID_19	-0.014***
	(0.012)		(0.001)
lnAirportVolume	0.004***	Density1COVID_19LCC	0.038***
	(0.001)		(0.003)
OwnHub	0.158***	Density2COVID_19LCC	0.001
	(0.001)		(0.003)
LocalOutbreak	-0.005***	Density3COVID_19LCC	0.002
	(0.001)		(0.003)
COVID_19	0.005***	LCCCOVID_19_t	-0.037**
	(0.000)		(0.017)
COVID_19_t	-0.014***	Density1COVID_19_t	0.000
	(0.003)		(0.009)
Density1LCC	-0.050***	Density2COVID_19_t	0.052***
	(0.002)		(0.005)
Density2LCC	-0.043***	Density3COVID_19_t	0.046***
	(0.002)		(0.004)
Density3LCC	-0.047***	Density1COVID_19_tLCC	-0.097***
	(0.002)		(0.029)
LCCCOVID_19	0.017***	Density2COVID_19_tLCC	0.011
	(0.002)		(0.027)
Density1COVID_19	-0.005***	Density3COVID_19_tLCC	0.011
	(0.001)		(0.022)
Observations	8,361,559	K-P rk Wald F statistic	2473
Carrier FE	Y	OD Route FE	Y
Departure city FE	Y	Arrival city FE	Y

Notes:

1. *, **, *** represent the 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parentheses.
2. Kleibergen-Paap rk Wald F statistic is from the weak identification test in the first stage regression of the 2SLS. The first-stage regression results are shown in Table A2.

Table 2.1.4 The estimated COVID-19 effects on route choices

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	0.055^{***}	-0.148^{***}
		(0.003)	(0.024)
	Density2	0.009^{***}	0.012
		(0.003)	(0.021)
	Density3	0.010^{***}	0.006
		(0.002)	(0.014)
	Others	0.022^{***}	-0.051^{***}
		(0.002)	(0.017)
The effect of the pandemic on FSCs route choice	Density1	0.0001	-0.014^{*}
		(0.001)	(0.008)
	Density2	-0.010^{***}	0.039^{***}
		(0.001)	(0.005)
	Density3	-0.009^{***}	0.032^{***}
		(0.001)	(0.004)
	Others	0.005^{***}	-0.014^{***}
		(0.0005)	(0.003)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	0.055^{***}	-0.134^{***}
		(0.003)	(0.023)
	Density2	0.019^{***}	-0.026
		(0.002)	(0.021)
	Density3	0.019^{***}	-0.026^{*}
		(0.002)	(0.014)
	Others	0.017^{***}	-0.037^{**}
		(0.002)	(0.017)

Notes:

1. *, **, *** represent the 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parentheses.
2. The coefficients presented in this table are calculated based on Table 2.1.3 and Table 2.1.1. The robust standard error of the "persistent effects" and "attenuating effects" can be calculated using the estimated variance-covariance matrix of the estimators of the individual parameters.

First, at the early stage of the pandemic, Chinese airlines were forced to withdraw their services from Density1 and Others routes, as shown by the significant negative attenuating effects for both Spring Airlines and FSCs. Airlines initially withdrew from routes linking with large cities that used to have larger air passenger volumes as well as small cities. This is probably because these major cities are also economic and political centers, so the pandemic control measures there were much stricter (e.g., Huang et al., 2020). Airlines exit from Others routes probably because of lower demand between secondary cities. The attenuating effect on FSCs shows that, at the beginning of the pandemic, FSCs quit Density1 and Others routes while serving more Density2 and

Density3 routes. With the market recovery, FSCs are more likely to enter Others routes, as shown by the significantly positive persistent effect. Compared with FSCs, Spring Airlines exited more dense routes. This can be observed from the larger absolute coefficients on Density1 routes (-0.148 vs. -0.014), indicating that Spring Airlines faced more stringent limitations, particularly during the initial stage of the pandemic outbreak. However, the negative impact has attenuated over time. Spring Airlines gradually added back the capacity and resumed network connectivity.

Table 2.1.4 also indicates a significantly positive persistent effect on Spring Airlines on all different categories of routes, implying that the airline has proactively and sustainably expanded its network since the pandemic outbreak, a trend that is consistent with the pattern depicted in Figure 2.1.3. Specifically, Spring Airlines is more inclined to enter Density1 routes, as evidenced by the largest coefficient for Density1. On the other hand, the persistent effect on Density1 routes for FSCs is found to be insignificant. This implies that FSCs have not substantially adjusted their route entry strategy on Density1 routes. In other words, FSCs had already been serving a large proportion of Density1 routes, with Air China, China Eastern, and China Southern already serving more than 40% of Density1 routes, and China Southern even exceeding 50% in December 2019. As a result, despite facing significant financial pressure during the pandemic, FSCs had limited room to adjust their strategy on these high-density routes. However, Table 2.1.4 reveals a significantly negative persistent impact on Density2 and Density3 routes for FSCs, while the impact on Others routes is significantly positive. These findings suggest that, in the long run, FSCs are more likely to exit from Density2 and Density3 routes and redirect their focus towards Others routes. This strategic shift may be attributed to the fact that FSCs previously concentrated on high-demand routes and international routes before the pandemic, but when the pandemic severely curtailed international travel, they pivoted to expand their networks into secondary cities, which they had previously overlooked.

These findings have important managerial and policy implications. Before the pandemic, Spring Airlines did not have a significant presence on these dense routes, either due to regulatory restrictions or to avoid head-to-head competition with FSCs. Spring Airlines preferred to explore the niche markets that link the secondary Chinese cities and expanded to the short-haul international routes to Northeast Asia and Southeast Asia. The pandemic has stopped the international expansion of Spring Airlines and forced them to focus on the domestic market again. The CAAC also lessened restrictions to allow more airlines to access the newly available slots at the major airports. Although Spring Airlines may still be concerned about retaliation from major FSCs in China, under very difficult financial conditions, they are more eager to enter those dense routes to quickly improve cash flow. Spring Airlines is able to adjust its competition strategies more quickly and flexibly than FSCs in response to the pandemic (Sun et al., 2022a). In addition, as we mentioned in the data description section, from September 2020 to December 2022, the feeder route access policy is valid. Although we do try to estimate the policy and pandemic impact, respectively, it is hard to divide them because this policy was announced to facilitate market recovery during the pandemic. The timing of the policy announcement closely coincides with the outbreak of the pandemic. Therefore, it is difficult to effectively estimate the respective impacts of the pandemic and the policy within a single estimation model. This is also one of the limitations of this study. As a result, our estimated pandemic impact in Table 2.1.3 captures the combined effects of the pandemic and the CAAC's policy influence.

We also created Figure 2.1.5 to show the net effect of the pandemic on Spring Airlines' route choice by aggregating the persistent and attenuating effects over time. After May 2020, Spring Airlines started to expand their entry into Density1 routes even more actively than before the pandemic.[16] Spring Airlines recovered very quickly from the initial negative impact of the pandemic and had become more aggressive in expanding their networks in the domestic market. As shown in Figure 2.1.5, Spring Airlines prioritized entering *Denstiy1* routes.

We observe slightly different recovery patterns for FSCs. During the initial stages of the pandemic, FSCs withdrew from Density1, Density2, and Density3 routes and instead focused on entering Others routes. This was influenced by the stricter pandemic control measures imposed on major hub airport cities during the early stages of the pandemic, while small cities were less impacted by the pandemic. But such patterns changed when

[16] Our econometric estimation is consistent with the real-world observation. As shown in the following news (in Chinese), in May 2020, the daily flight volume of Spring Airlines, surpassed the highest level before the pandemic. See http://www.caacnews.com.cn/1/6/202105/t20210508_1323641.html.

the pandemic gradually came under control. FSCs recovered their service on Density1 routes and continued to expand their services on Others routes. We also plot the net effect of the pandemic on FSCs' route choices, as shown in Figure 2.1.6.

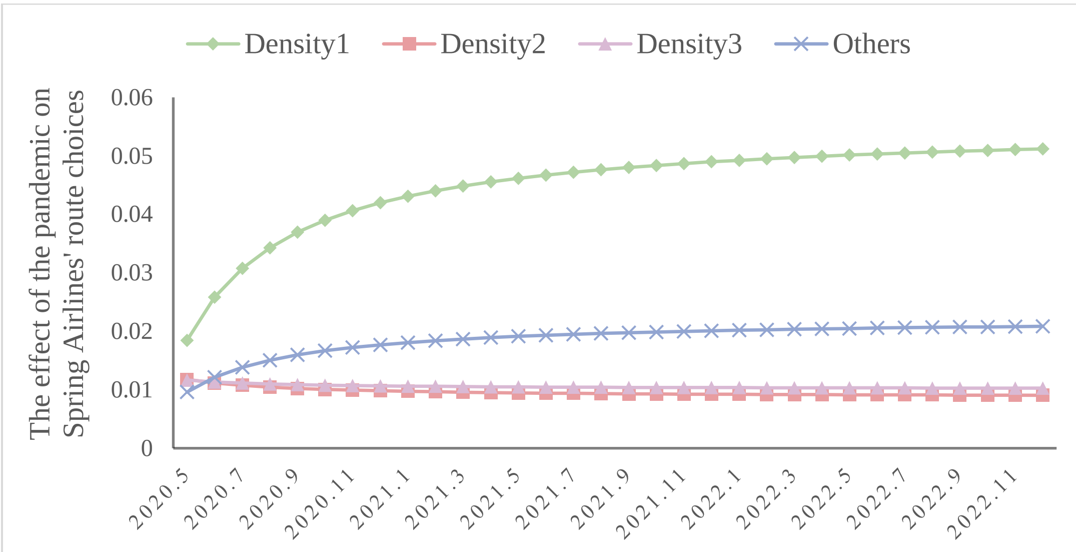


Fig. 2.1.5: The net effect of the pandemic on Spring Airlines' route choices

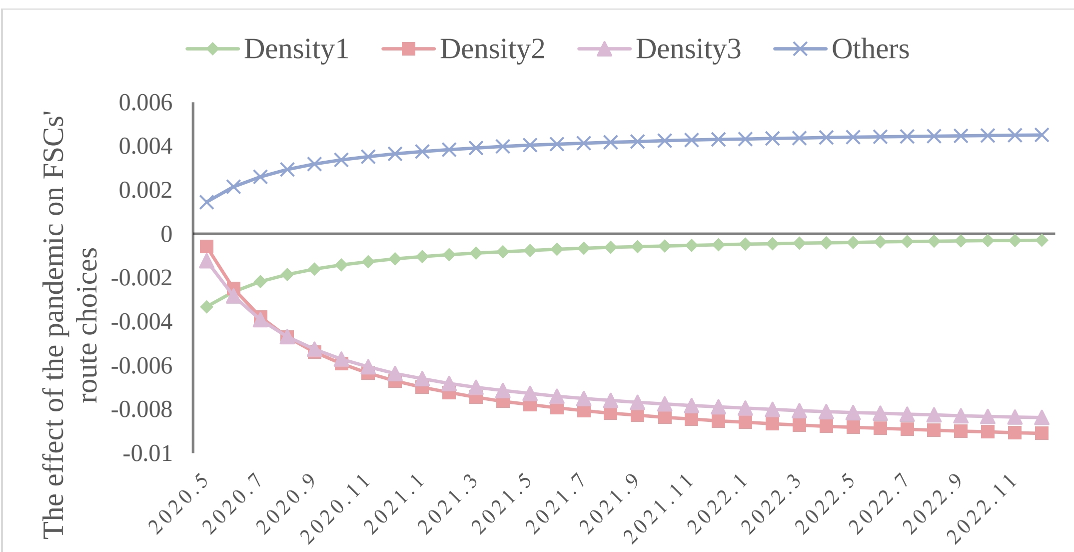


Fig. 2.1.6: The net effect of the pandemic on FSCs' route choices

Finally, Table 2.1.4 also directly compares the impact of the pandemic on FSCs and Spring Airlines. For a clear illustration, Figure 2.1.7 exhibits the differences in the net effect of the pandemic between Spring Airlines and FSCs. It is clear that Spring Airlines is more active than FSCs in entering the dense routes during the pandemic, especially on Density1 routes. Such differentiation in route choice patterns during the pandemic is likely to reshape the competition structures between FSCs and Spring Airlines. Those dense routes were previously dominated by FSCs, especially in relation to the hub airports in Beijing, Shanghai, and Guangzhou. With Spring Airlines entries into these routes, head-to-head competition would become more frequent and fiercer between these carriers.

To further examine the variation in market contact and the change in market dominance on different types of routes, we conduct a further empirical investigation using the multinomial discrete choice model in the next subsection.

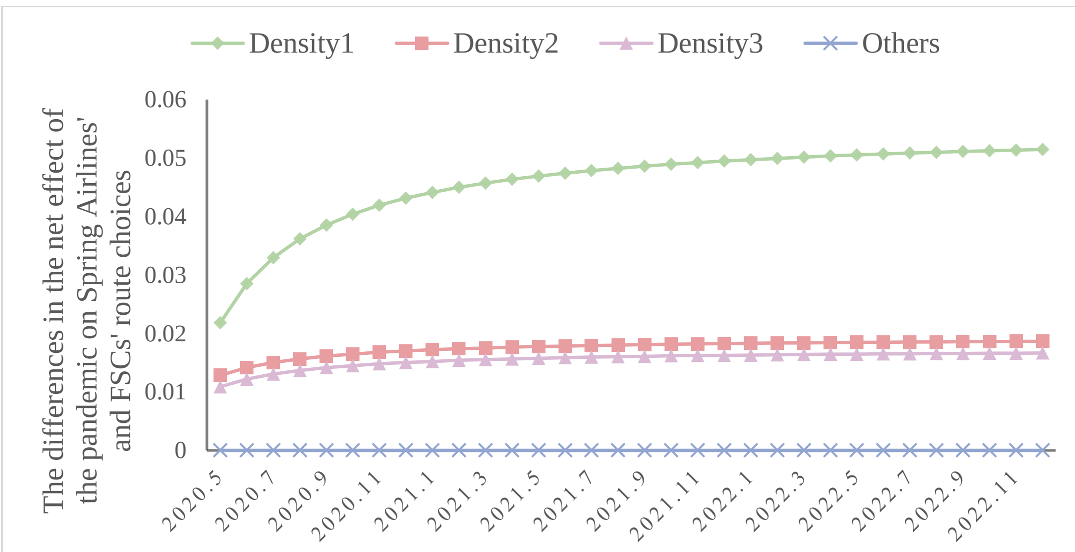


Fig. 2.1.7: The differences in the net effect of the pandemic on the route choices of Spring Airlines and FSCs

From the above discussion, we found that after the outbreak of the pandemic, Spring Airlines and FSCs have implemented distinct route service strategies. Both have actively entered dense routes, but Spring Airlines has pursued a more aggressive expansion of its network compared to FSCs. This could be attributed to the different financial circumstances and fleet compositions and the policy support. Spring Airlines has a relatively low international route ratio, typically less than 10%. The fleet composition of Spring Airlines consists entirely of A320 aircraft, which allows for more flexibility in reallocating these aircraft to domestic routes. According to the annual reports of airlines, the “Big Three” experienced significant losses following the pandemic, with a total loss amounting to as much as 100 billion yuan in 2022. Unlike Spring Airlines, FSCs generally have a higher proportion of international routes and operate a larger number of wide-body aircraft. During the pandemic, FSCs operated wide-body aircraft on domestic routes to generate revenue and mitigate substantial losses. However, profitability for wide-body operations is only feasible on dense routes. Therefore, FSCs have also quickly recovered their service on dense routes to increase their operating income. For example, China Southern Airlines made adjustments to its operations. In September, they deployed wide-body A330 aircraft on the Shenyang-Chengdu route. Furthermore, in December 2020, they used a B787 aircraft for the first time to operate a domestic route from Shenyang to Guangzhou [17]. As for policy support, before the pandemic, CAAC imposed strict restrictions on small airlines operating routes connecting to Beijing, Shanghai, and Guangzhou. However, the pandemic caused significant losses for these small airlines, particularly independent LCCs, without direct government financial support. Nine months after the outbreak of the pandemic, CAAC lowered the requirements for entry into the Beijing, Shanghai, and Guangzhou markets, aiming to assist airlines in surviving the crisis. Spring Airlines seized this opportunity and expanded its operations to nine routes that were previously inaccessible to it.

Unlike state-owned FSCs, Spring Airlines is a privately-owned airline. These FSCs receive substantial financial support from the government in the form of subsidies to sustain their operations. Subsidies received by the three major airlines were nearly ten times higher than those received by Spring Airlines. However, the government may adopt a more cautious approach in providing financial assistance to privately-owned airlines but may still seek alternative measures to relax regulations and support their survival, such as easing route entry restrictions in September 2020. Once the CAAC released the restriction, Spring Airlines promptly entered these newly accessible routes to capitalize on the potential revenue. The number of Density1 routes served by Spring Airlines in 2022 is three times higher than the number in 2019. According to its annual report, Spring Airlines achieved a net profit of 39 million yuan in 2021. This indicates that their expansion on dense routes and overall network expansion proved to be successful in improving their

[17] See relevant news report (in Chinese) at https://ln.chinadaily.com.cn/a/202012/25/WS5fe557a6a3101e7ce973769f.html.

financial performance. Furthermore, the increased presence of Spring Airlines on Density1 routes, which were traditionally dominated by FSCs, has indeed pushed FSCs to work harder to maintain their competitiveness and connectivity on these routes. This has intensified the competition on Density1 routes between Spring Airlines and FSCs.

2.1.5.3 Market contact between FSCs and Spring Airlines

Given the observed heterogeneous impacts of the pandemic on the route choices of FSCs and Spring Airlines, the market contact between FSCs and Spring Airlines could also have been reshaped as a result. In Table 2.1.5, we categorize the routes into three groups, namely "*Spring Airlines monopoly*," "*FSC monopoly,*" and "*Overlap*."[18] The share of the number of routes in the FSCs-Spring Airlines competition (i.e., *Overlap*) increased on the *Density1* routes, from 2.8% to 7.1%. This is consistent with our previous finding that Spring Airlines has been more aggressive in entering the dense routes linking the hub airports after the outbreak of the pandemic. This implies more direct competition with the incumbent FSCs. Such intensified competition on these dense routes is likely to further reduce ticket prices and stimulate traffic growth. However, FSCs could experience more serious financial difficulty, as Spring Airlines possesses a clear cost advantage and can compete effectively with FSCs. Indeed, the share of *LCC monopoly* also rose from 2.0% to 3.2%. These patterns explain the deteriorating financial performance of FSCs in 2020 and 2021. The carriers continuously reported huge financial losses, although domestic airline traffic had almost recovered to pre-pandemic levels. In contrast, Spring Airlines reported only a mild financial loss in 2020 and even achieved a positive profit in 2021. Meanwhile, we cannot observe a clear change in the shares of *Overlap* routes in Others types of routes (see Table 2.1.5). In other words, after the pandemic, the intensified competition between FSCs and Spring Airlines has been concentrated more on the *Density1* routes involving the hub airports. But further verification through an econometric model is needed to avoid confounding factors.

[18] "FSC monopoly" routes are those served only by FSCs; "Spring Airlines monopoly" routes are those served by Spring Airlines but not served by FSCs; and "Overlap" routes are those served by both FSCs and Spring Airlines.

Table 2.1.5 Comparison of market structure before and during the pandemic

Route category	Market structure	Before pandemic	Late stage of pandemic
Density1	Spring Airlines monopoly	2.0% (24)	3.2% (42)
	FSC monopoly	77.9% (956)	69.6 % (926)
	Overlap	2.8% (34)	7.1% (94)
Density2	Spring Airlines monopoly	0.7% (6)	1.8% (16)
	FSC monopoly	77.8% (658)	76.5% (690)
	Overlap	2.8% (24)	4.2% (38)
Density3	Spring Airlines monopoly	1.2% (18)	1.1% (18)
	FSC monopoly	80.3% (1248)	75.5% (1226)
	Overlap	1.7% (26)	3.3% (54)
Others	Spring Airlines monopoly	4.2% (74)	7.2% (154)
	FSC monopoly	77.7% (1362)	70.4% (1511)
	Overlap	4.7% (82)	5.6% (120)

Notes:
1. "Before pandemic" is calculated with the data as of December 2019; "Late stage of pandemic" is calculated with the data as of December 2022;
2. The number in parentheses is the number of routes;
3. The Spring Airlines monopoly refers to the routes that are exclusively served by Spring Airlines. These routes are not served by any FSCs. Overlap refers to the routes that are served by Spring Airlines and FSCs. It's important to note that the sum of each category of routes is less than one, as there are other market structures, such as overlapped routes between other LCCs and FSCs.

Next, we estimate a multinomial model to directly measure the impact of the pandemic on market contact between FSCs and Spring Airlines. Specifically, it quantifies both the attenuating and persistent effects of the pandemic to alter the composition of *Spring Airlines monopoly*, *FSC monopoly,* and *Overlap* for each type of route in the Chinese domestic market. The dependent variables of the multinomial model are the discrete variables indicating the three competition structures, namely *Spring Airlines monopoly*, *FSC monopoly,* and *Overlap*. The variables $COVID19_t$ and $\frac{1}{COVID19_{t_t}}$ are used to capture the persistent and attenuating effects, which are analogous to the discrete choice model in subsection 2.1.5.1. Since this multinomial model is estimated at the route level, the control variables are also set at the route level, including $AirportVol_{it}$, $Dist_i$, $Airport_{HHI_{it}}$, $LocalOutbreak_{it}$. Similar to the route choice model, we also incorporate a series of interaction terms to capture the heterogeneous impacts of the pandemic on airline market contact on different types of routes. Maximum Likelihood Estimation (MLE) is adopted to estimate the multinomial model.

The complete coefficient estimations of this multinomial model are reported in Table 2.1.6. The multinomial model estimation sets *FSC monopoly* as the base case, such that the estimated coefficients indicate the probability difference to obtain *Spring Airlines monopoly* or *Overlap* when compared to *FSC monopoly*. Table 2.1.7 summarizes the results of the change in probability of *Spring Airlines monopoly* and *Overlap* before and after the pandemic. Our focus is on the persistent effect, which suggests a relatively long-term impact of the pandemic on market competition structures. It is interesting to observe that the probability of *Overlap* (i.e., head-to-head FSC and Spring Airlines competition) has been significantly increased on all types of routes during the pandemic, while the degree of the impact on *Density1* routes is the largest (with the coefficient estimated as 1.813). We also see a significant increase in the probability of *Spring Airlines monopoly* on *Density1* routes (a significant coefficient of 0.641). This result confirms our previous arguments about more intensified competition between FSCs and Spring Airlines after the outbreak of the pandemic, in particular on *Density1* routes. Similar results hold for *Density2, Density3, and Others* routes, but the increase in competition between FSCs and Spring Airlines is less than that on *Density1* routes. The above discussions can be better illustrated by Figure 2.1.8, which summarizes the net effect of the pandemic on the market competition structure.

Based on the estimated persistent and attenuating effects (see Table 2.1.7), we also calculated the net effect of the pandemic on market contact between FSCs and Spring Airlines. Spring Airlines tried to enter more dense routes linking FSCs' hub airports during the pandemic. As a result, market competition in the Chinese domestic market has intensified, with airlines breaking the pre-pandemic equilibrium of market coverage differentiation in efforts to explore any opportunity to recover revenue under stressful financial conditions.

Table 2.1.6 The estimation results of multinomial model (with FSC_monopoly as the base)

VARIABLES	(1) Spring Airlines monopoly	(2) Overlap
lnAirport_HHI	-0.323***	-0.140***
	(0.0383)	(0.0395)
lnAirportVolume	0.122***	-0.0245**
	(0.0109)	(0.0106)
lnRoute_HHI	3.861***	-3.238***
	(0.105)	(0.0278)
lnDistance	0.437***	0.475***
	(0.0250)	(0.0252)
Local Outbreak	0.156	0.172**
	(0.110)	(0.0793)
COVID_19	0.686***	0.465***
	(0.0450)	(0.0493)
COVID_19_t	-2.325***	-0.372
	(0.363)	(0.406)
Density1	-0.643***	-1.357***
	(0.0714)	(0.0649)
Density2	-1.210***	-1.855***
	(0.101)	(0.0764)
Density3	-1.451***	-1.907***
	(0.0833)	(0.0663)
Density1*COVID_19	-0.0454	1.348***
	(0.0911)	(0.0777)
Density2*COVID_19	-0.272**	0.205**
	(0.134)	(0.101)
Density3*COVID_19	-0.352***	0.380***
	(0.110)	(0.0872)
Density1*1/COVID_19_t	0.971	-5.976***
	(0.726)	(0.614)
Density2*1/COVID_19_t	1.599	-0.885
	(1.067)	(0.805)
Density3*1/COVID_19_t	2.461***	-1.749**
	(0.850)	(0.704)
Constant	-9.105***	-6.932***
	(0.255)	(0.250)
Observations	261,912	261,912

Note: *, **, *** represent the 10%, 5% and 1% significance levels. Standard errors in parentheses.

Table 2.1.7 The estimated COVID-19 effects of the multinomial discrete choice model

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	0.641^{***}	-1.354^{**}
		(0.079)	(0.629)
	Density2	0.415^{***}	-0.727
		(0.127)	(1.003)
	Density3	0.334^{***}	0.136
		(0.101)	(0.769)
	Others	0.686^{***}	-2.325^{***}
		(0.045)	(0.363)
Overlap before and after the outbreak of the pandemic	Density1	1.813^{***}	-6.349^{***}
		(0.060)	(0.460)
	Density2	0.669^{***}	-1.258^{*}
		(0.089)	(0.695)
	Density3	0.845^{***}	-2.121^{***}
		(0.072)	(0.576)
	Others	0.465^{***}	-0.372
		(0.049)	(0.406)

Notes:
1. *, **, *** represent the 10%, 5%, and 1% significance levels, respectively.
2. The standard deviation of the function of the coefficient estimators can be obtained through the delta method, such that the statistical inference (i.e., the significance level) can be conducted.
3. The observation number for this estimation is 261,912.

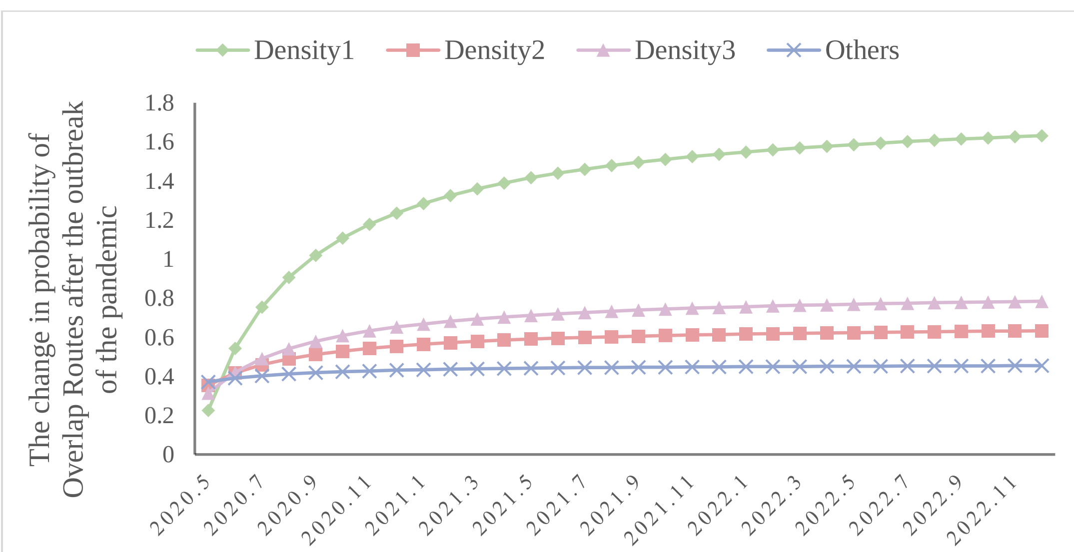


Fig. 2.1.8: The change in the probability of Overlap Routes during the pandemic

2.1.5.4 Robustness checks

This subsection presents some robustness checks to demonstrate that our empirical findings are consistent under alternative variable definitions. Although the *K-means* method suggests grouping the top five cities with the largest air passenger volume as *Density1* routes, we notice the top three cities, namely Beijing, Shanghai, and Guangzhou, appear to be more distinct than others. These cities are Chinese international airline gateways and are the main hubs of the Big Three airlines. Therefore, we re-defined *Density1* routes as those connected only with these top three cities. *Density2* routes are thus those connecting the 4^{th}-10^{th} cities. *Density3* and *Others* routes remain the same as before. The regression results of the linear probability model and the multinomial model are reported in Table A3(a) and Table A3(b). Both the persistent effect and attenuating effects of the pandemic on FSCs' and Spring Airlines' route choices do not qualitatively change. When comparing Table A3(a) and Table A3(b) with Table 2.1.4 and Table 2.1.7, we found that Spring Airlines has a more significant persistent effect in expanding into *Density1* routes that link with the top three cities (i.e., Beijing, Shanghai, and Guangzhou) (0.083 vs. 0.055 in Table 2.1.4). Spring Airlines has been even more active in expanding its routes in these top three cities than FSCs. As these three cities are the major hubs of the Big Three airlines, it is intuitive that market contact between FSCs and Spring Airlines has increased.

Another more straightforward approach is to divide the routes based on route-level passenger volume, not the endpoint cities. We used *K-means* clustering based on route-level passenger traffic to divide the routes. Now, *Density1*, *Density2*, *Density3*, and *Others* are based on the route-level passenger volume. The regression results are reported in Tables A4(a) and A4(b) and do not qualitatively change. We still identify a significant attenuating effect and a positive persistent effect of the pandemic.

We also used alternative variable forms to capture the attenuating effect. Specifically, we tried $\frac{1}{(COVID19_{t_t})^2}$ and $\frac{1}{\sqrt{COVID19_{t_t}}}$. $\frac{1}{(COVID19_{t_t})^2}$ stands for a faster attenuating effect, while $\frac{1}{\sqrt{COVID19_{t_t}}}$ stands for a slower attenuating effect. The estimation results using $\frac{1}{(COVID19_{t_t})^2}$ are collated in Table A5(a) and Table A5(b). The persistent and attenuating effects of the pandemic are statistically significant. The results on the FSCs and Spring

Airlines are also qualitatively consistent with those by using $\frac{1}{COVID19_{t_t}}$. Market contact between FSCs and Spring Airlines is found to have increased significantly after the outbreak of the pandemic (see Table A5(b)). The estimation results also do not change qualitatively when using $\frac{1}{\sqrt{COVID19_{t_t}}}$ (see Tables A6(a) and A6(b)).

We also conducted a placebo test for the period January 2019 to December 2019 and assumed the pandemic shock in July 2019. The regression results are shown in Tables A7(a) and A7(b). The test indicates that the simulated pandemic shock has no significant impact on airlines' route entry decisions, further validating our estimated pandemic's impacts.

To analyze the persistent effect more precisely, we have conducted a robustness test by utilizing a sub-sample of our data in December 2019 and December 2022 by excluding the routes with temporary shutdowns rather than permanent withdrawals, namely those routes that were quit by airlines when the pandemic broke out, while later re-entered by the same airlines. It is found that the estimation results do not change significantly. Specifically, when doing this robustness check, if the route is newly entered by the airlines, the binary variable is equal to 1. If the route is not re-entered, the binary variable is equal to 0. Apart from the market-related control variables, the interaction terms of LCC and Density_i are also added. The regression results are presented in Table A8. The significantly positive coefficients of the interaction term of LCC and Density_i indicate that, in comparison with FSCs, the persistent effect of the pandemic on Spring Airlines is significantly positive. This implies that Spring Airlines tends to focus on serving denser routes.

Overall, robustness checks have shown that our major empirical findings are quite strong. After the outbreak of the pandemic, Chinese airlines, both FSCs and Spring Airlines, have adjusted route choice strategies that are affected by the characteristics of the endpoint airports. The airlines, especially Spring Airlines, have become more aggressive in expanding their networks, mainly on those dense routes that were previously dominated by FSCs.

2.1.6 Summary

This section empirically examines the impact of the pandemic on airlines' route choice and market contact in the Chinese domestic market. An airline route discrete choice model is estimated for both FSCs and Spring Airlines. The estimation disentangles the attenuating and persistent effects of the pandemic on airlines' route choice. The former effect refers to airlines' initial route exits in response to a sudden decline in air travel demand and strict pandemic controls, while the latter effect reflects the airlines' relatively long-term adjustment of competition strategy triggered by the pandemic. Our empirical findings are as follows: The pandemic had a positive "persistent effect" and a negative "attenuating effect" on Spring Airlines. Spring Airlines has actively expanded its network to all types of routes, especially the dense routes connected to major airports. FSCs also adjusted their route entry strategy by entering more thin routes connected to secondary cities (i.e., a positive "persistent effect"). The pandemic has broken the pre-pandemic equilibrium of network differentiation between FSCs and Spring Airlines. Spring Airlines began to expand its services at FSCs' major hub airports, while FSCs also try to explore the lucrative niche routes previously dominated by LCCs. Overall, we observe more frequent market contact and increasing head-to-head competition between FSCs and Spring Airlines as the pandemic is under control. This is probably because of the airlines' desperate financial difficulties, which have forced them to increase competition. It is also facilitated by more idle aircraft/airport slot capacities re-allocated from the international market to the domestic market due to the CAAC's tight regulation of international services following China's zero COVID policy.

Our study supplements the findings of previous literature with new insights and contributions. This is the first empirical study to disentangle the attenuating and persistent effects of the pandemic on airlines' route choice. Second, we measured the change in market contact between FSCs and Spring Airlines in the Chinese domestic market. Although the study is carried out in the context of the Chinese market, the implications may provide different perspectives for analyzing other major and emerging airline markets of similar size and legacy regulations.

Despite the large sample size and robustness checks, this study is still subject to some limitations, while opening avenues for future studies. First, our study focuses on the overall competition pattern between FSCs and Spring Airlines, but does not look into each specific airline's competition decisions. As the Chinese domestic market is dominated by the Big Three airlines, their mutual competition interactions have likely been affected by the pandemic and deserve a closer examination in future studies. Second, as explained in our data description section, the ticket price and passenger traffic data were subject to significant measurement errors during the pandemic. Thus, we chose not to estimate the airline price and demand functions. If more accurate and reliable data can be obtained, relevant studies can be conducted to offer additional results from different perspectives. Third, since September 2020, CAAC has lessened the entry restriction of feeder routes connecting with major hub airports in China, namely Beijing, Shanghai, and Guangzhou. We have tried to explicitly disentangle this specific CAAC deregulation policy from the estimated overall pandemic impact. However, it proves hard to empirically identify such policy effects with our dataset. Since the deregulation policy could also take some time to be effective as airlines also need time to respond, it is difficult to specify the time point for CAAC policy in the empirical analysis. Thus, when defining the CAAC policy to be effective from September 2020, our empirical results cannot obtain the significant policy effect estimations. This is also partly because the policy implementation is closely correlated with the pandemic periods. Therefore, the route choice effect this study estimated is the combined impact of the pandemic and CAAC deregulation policy. Fourth, although we attempted to minimize potential biases resulting from omitted variables by including control variables, fixed effects, and using IV methods, this study may still be subject to potential estimation bias. For example, we have not considered the possible heterogeneous impact of the pandemic on different FSCs. That said, our estimation mainly reflects the average impact. Additionally, omitted variables at the airline level, such as the airline network scale, the share of domestic routes, and international routes before the pandemic, could also affect our estimation results. Other variables, such as weather conditions over time, can also potentially impact airlines' route entry decisions. However, due to limitations in data availability, this study is unable to control for all of these factors. A more in-depth analysis of the heterogeneous pandemic impact on airlines could be explored in future studies when the data is available and leverage on more sophisticated econometric models. Finally, we only chose data up until the end of 2022. Our findings may not be generalized in a much longer period post-pandemic, especially when the Chinese government has already fully lifted its border control. When international flight services and networks resume, the major Chinese airlines will resume their international services and thus re-adjust their domestic market competition strategy. We hope our study can lead to more advanced empirical approaches and research designs to overcome such limitations. All these areas are meaningful extensions but are beyond the scope of the current study.

2.2 Impact of the COVID-19 Pandemic on Multi-Airport Systems Worldwide

2.2.1 Abstract

This study examines the impacts of the COVID-19 pandemic on multi-airport systems (MASs) worldwide. First, the recent literature on MASs is reviewed to identify emerging research topics and development patterns. Then, airline schedule data are collected for 53 sample MASs and used to analyze three dimensions of MAS structures before and during the late stage of the pandemic: (i) traffic and degree centrality distribution within MASs, (ii) intra-MAS airport competition; and (iii) airline competition intensity within MASs. The empirical findings reveal that MAS structures in Europe and the US have remained relatively stable despite the recent pandemic, partly because compared with Asia Pacific, air travel bans in these markets were lifted earlier, and domestic and international airline markets have largely returned to pre-pandemic levels. In comparison, significant changes have been observed in Asia-Pacific MASs due to restrictive bans on international travel and airline operations. As major airlines shifted capacity to domestic markets, in Asia Pacific intra-MAS airport traffic distribution became more balanced, intra-MAS airport competition intensified, smaller airlines dropped out, and airline concentration levels increased. In addition, with more under-utilized slots available, Chinese low-cost carriers increasingly consolidated their operations to selected airports within MASs which would allow them to achieve economies of scale. Overall, this study provides insights into the adaptability of MAS structures in the face of a global crisis.

2.2.2 Introduction

The air transport industry's rapid growth in recent decades has led to the fast development of multi-airport systems (MASs) around the world. In addition to well-known systems in London, New York, Tokyo, and Paris, emerging countries with booming airline markets, particularly China, have also developed MASs (Hou et al., 2022a). MASs not only alleviate airport capacity constraints but also optimize airline services and connectivity for metropolitan areas. Some MASs have airports serving distinct market positions to diversify the airline services in one metropolitan area. At the same time, the inter-airport competition within MASs can reduce airfares and increase flight frequencies, benefiting passengers and regional economies (Winston and Yan, 2011). A well-functioning MAS thus stimulates air traffic and coordinates economic development within and across regions (Brueckner, 2003a; Sheard, 2014). The strategic interactions among airports and airlines are more complex in the presence of MASs, involving decisions about flight frequency, airfares, airport entries, and network development. Passengers' airport choices depend on factors such as ground access, flight networks, schedules, and airfares. Previous studies have documented these issues through theoretical and empirical approaches, as summarized and discussed in Section 2.2.3.

The COVID-19 pandemic (hereafter referred to as "the pandemic") has had unprecedented impacts on the entire airline industry, and extensive research has been conducted to understand its effects from different perspectives (Sun et al., 2020; Nižetić, 2020; Suzumura et al., 2020; Zhang et al.,2021; Czerny et al. 2021). Existing studies of the pandemic's impact on airport operations have mainly focused on individual airports of different sizes and regions. Travel restrictions have severely damaged international connectivity for major regional gateway airports worldwide, while domestic aviation markets have generally recovered as outbreaks have been contained domestically, despite several waves of local outbreaks. The pandemic's impact on airports may also depend on their network structure, such as hub-and-spoke vs. point-to-point, as well as the type of airlines (full-service carriers (FSCs) vs. low-cost carriers (LCCs)) and airline dominance at a particular airport, because such factors are likely to moderate the pandemic's effect on airport operations, airline competition and dominance, and network configuration (Fu et al. 2015a, 2019).

Despite extensive research on the impacts of the pandemic on the air transport industry, there has been relatively little investigation into how MASs have been affected. Many questions remain unanswered in this area. First, the pandemic could have affected different airports in the same MAS differently, causing changes in traffic and connectivity distributions among individual airports. Second, inter-airport competition within MASs might have been affected, with market coverage converging (serving more common destinations) or diverging (serving fewer common destinations) during the pandemic. Last, the pandemic could have caused variations in airline competition (including that among airlines providing differentiated services, such as FSCs vs. LCCs (Fu et al. 2011)) and their dominance among different airports (such as an airport's hub status). For example, London's metropolitan area is served by six international airports, with Heathrow (LHR) dominated by British Airways and Gatwick (LGW) as a main base for Easyjet, a low-cost carrier. The pandemic is likely to have imposed heterogeneous impacts on these airports within the London MAS, which could have significant implications on airline competition, airport capacity/slot use, and airport connectivity. The pattern and magnitudes of such impacts nevertheless remain unclear to industry and policy makers. This study aims to address these gaps in the literature by examining the impacts of the pandemic on MASs worldwide, shedding light on the changes and development patterns of these systems.

To address the research questions outlined above, we collected airline scheduled seat data for 53 MASs worldwide over the 2018-2022 period. Several statistics and indices were calculated and benchmarked before and during the late stage of the pandemic, with a focus on the relatively long-term impact of the pandemic. We conducted an intra-MAS analysis to examine the heterogeneous impacts of the pandemic on the traffic and network size of airports within the same MAS, calculating the Gini index of scheduled capacity and the degree of centrality for each MAS. Additionally, we constructed a Herfindahl-Hirschman Index (HHI) using the capacity share of flights with the same destination but originating from different airports within an MAS, to measure the level of intra-MAS airport competition. We were also interested in checking the change in this index during the pandemic. To examine inter-airline competition, particularly between FSCs and LCCs within an MAS, we calculated and compared the Gini index of the airlines' market shares in each MAS before and during the late stage of the pandemic. We conducted these analyses for each sample MAS and conducted cross-regional comparisons to shed light on heterogeneous patterns among different regions worldwide, including the US, Europe, and the Asia-Pacific.

The remainder of this study is structured as follows. Section 2.2.3 provides a review of the relevant literature on MAS published in recent years, revealing recent MAS developments and relevant research hotspots worldwide. Section 2.2.4 describes the data used in this research, including the definition and selection of sample MASs for this study. In Section 2.2.5, we conduct a series of calculations based on the statistics and indices described in the previous paragraph and provide a discussion and interpretation of the results. Finally, Section 2.2.6 provides concluding remarks for this study.

2.2.3 Literature Review

This section presents a review and summary of the recent literature on MAS development, with a focus on academic publications in the past decade (since 2013) related to MAS management and economic issues. Relevant studies can be broadly categorized into two categories: those investigating passengers' airport choices within an MAS and those examining airline/airport competition within an MAS. Additionally, we review recent studies of the impacts of the pandemic on airport operations, which should provide useful insights into the impacts on MASs.

2.2.3.1 Passengers' airport choices in MASs

Since the 1980s, it has been a common research strategy to examine passengers' airport choices within an MAS. Analytical and empirical research has explored the factors influencing passengers' airport choices, with a focus on some major MASs in the US and Europe, particularly San Francisco, New York, and London (Harvey, 1987; Pels et al., 2000, 2001, 2003; Hess et al., 2006; Marcucci and Gatta, 2011, 2012; Murça et al., 2013). These studies suggest that the ground access time and cost, flight frequency, and flight time play important roles in determining passengers' airport choices, with passengers exhibiting heterogeneous preferences for different factors.

In recent years, an increasing number of researchers have paid attention to MASs in developing countries, such as China, Iran, Slovenia, and Brazil. Table 2.2.1 summarizes papers on this topic published in the last decade, which focused on different factors that shape passengers' airport choices. In addition to the aforementioned influencing factors, recent studies have also considered new factors related to passengers' perceptions of service quality, such as safety and punctuality, which also contribute significantly to passengers' choice decisions. Some studies investigate air-rail intermodal transport for MAS connectivity and its influence on passengers' airport choices. Both theoretical and empirical studies have suggested that passengers choose air-rail intermodal transport if one airport has better integration with high-speed rail (HSR) service, such as Hongqiao Airport in Shanghai MAS and Daxing Airport in Beijing MAS, due to considerations related to the contingency arrangement in case of delays and regarding checking-in, comfort, and luggage deposits (Chiambaretto et al., 2013; Li et al., 2020; Wang et al., 2020b; Babić et al., 2022).

Table 2.2.1 Recent literature on passenger airport choice in MAS

Author/Year	Studied MAS	Model Specifications/Findings
Fuellhart et al. (2013)	Boston, Washington, and San Francisco, the US	Higher route-level airfares and longer route distance lead to an apparent switching of passengers' airport choices. This suggests passengers are more likely to switch to a preferred airport for long-haul travel.
Mamdoohi et al. (2014)	Tehran MAS, Iran	Binary Logit model; Focus on the difference of airport choice between resident and non-resident and find that public access, flight frequency, and airport tax are more important for non-resident air travelers when choose their departure airport.
Paliska et al. (2016)	Upper Adriatic region, Slovenia	Mixed logit model; Access time to the airport is the key factor influencing airport selection for all types of travelers, whether business or leisure, and whether for domestic or cross-border trips. Borders also affect the choice of airport.
Jung and Yoo (2016)	Seoul MAS, South Korea	Two-level Nested Logit model; The analysis reveals significant impacts of fare, flight time, frequency, access characteristics (time/cost), and accessibility-related latent variables on airport choice behavior.
Bezerra and Gomes, (2019)	São Paulo MAS, Brazil	Partial least squares–structural equation model; Support airport service quality as a determinant of passenger loyalty. Marketing and operational strategies based on customer

		segmentation help to strengthen the passenger loyalty to the airport.
Tiglao (2020)	Aklan MAS, Philippines	Discrete choice model; Tourist passengers place a high value on air safety.
Teixeira and Derudder (2021)	New York MAS, the US	Huff models; Examine the spatio-temporal dynamics within airport catchment areas and assess airport attractiveness to passengers across various census block groups.
Liao et al. (2022)	Guangdong-Hong Kong-Macao Greater Bay Area (GBA), China	Partial least squares structural equation model; Confirm positive relationships between airport service quality and passengers' intention to reuse an airport.

2.2.3.2 Airline or airport competition in MASs

As mentioned in the introduction, the presence of an MAS enhances strategic interactions among airports in a region and intensifies both inter- and intra-airport airline competition. In recent years, researchers have paid increasing attention to the privatization of one or more airports within an MAS, following the global trend towards airport corporatization (Noruzoliaee et al., 2015). This trend has been particularly notable in China, where several airports have consolidated to form airport group companies to improve profitability and achieve better coordination. Furthermore, the prevalence of HSR has significantly reshaped the intercity transport market, particularly in China. The integration of air and HSR transport with some airports within an MAS can significantly affect airport and airline competition and coordination behaviour. Recent studies have investigated the impacts of these developments on MASs and their implications for airport and airline operations and competition. Table 2.2.2 provides a summary of these studies published over the past decade.

Table 2.2.2 Recent literature on inter-airport and airline competition in MAS

Author/Year	Studied MAS	Model Specifications/Findings
Yan and Winston (2014)	San Francisco Bay area, the US	Focus on private airport competition and find that it enhances the welfare of commercial travelers, boosts airline profits, and enables airports to become profitable.
Liao et al. (2019)	Guangdong-Hong Kong-Macao Greater Bay Area (GBA),	Three liner models; Focus on the route level competition between airports in GBA-MAS and its impact on passenger airport choice.

	China	
Wong et al. (2019a)	MAR around world	With the competition of FSCs, LCC shift focus from smaller airports in MAR to non-MAR airports.
Wong et al. (2019b)	MAC around world	Discuss the competition for passengers between hub airports and secondary airports in multi-airport cities.
Cheung et al. (2020a)	Guangdong-Hong Kong-Macao Great Bay Area MAS, China	The dynamic spatial panel regression model offers a new approach to studying airport competition. This paper focuses on spatial interactions and spillover effects in the context of airport competition.
Hou et al. (2022a)	Beijing MAS, China	Multi-stage game-theoretical model; Focus on the impact of government intervention on airport competition. Find that without government intervention in airline allocation between the two airports, airlines would always prefer to enter both airports in the MAS, leading to both an inter-airport and an intra-airport competition structure.
de Paula Balan et al. (2022)	São Paulo and Rio de Janeiro MAS, Brazil	The growing overlap of routes in MASs has fostered healthy competition between airports and airlines over the years.
Li et al. (2022a)	Theoretical analysis	Investigates the impact of cooperation between air travel and high-speed rail (HSR) on airport competition in MASs and its implications for social welfare.

2.2.3.3 The impact of the pandemic on the airport

The pandemic has had an unprecedented impact on the aviation industry, as evidenced by recent studies (Zhang et al., 2020a; Sun et al., 2020; Czerny et al., 2021; Sun et al., 2021a; Salesi et al., 2022). Researchers have conducted numerous investigations into the pandemic's effects on airport connectivity and operations and its heterogeneous impacts across different airports and regions. Sun et al. (2022b) provided a comprehensive review of the research on the pandemic and air transport. Specifically, regarding the impact on airport operations, many studies have focused on the passenger travel experience during the pandemic. For example, Li et al. (2022b) used a data-driven crowd-sourcing approach to study airport service quality during the pandemic. Ma et al. (2022) built a structural equation model to investigate the influences of four attributes of the airport physical environment on passengers' perceived safety, satisfaction, and travel intentions during the pandemic. Zhang et al. (2021) used passengers' air ticket booking transaction data and airport arrival data to empirically examine passengers' travel behaviors during the pandemic and found that passengers arrived at the airport earlier to undergo health check procedures, despite having fewer opportunities to shop and dine at airports. Chen (2022a, b) also found very obvious empirical evidence for the substitutability of online meetings for air travel among heterogeneous traveler, which could also cause changes in passenger composition and air travel behavior during and after the pandemic.

Many researchers have focused on the impact of the pandemic on airport connectivity and have found that airport networks changed significantly during the pandemic. These changes include shifts in airport degree centrality, international connections, and network connectivity (Sun et al., 2020, 2021b; Li et al., 2021; Kuo et al., 2022). Several studies have concluded that the pandemic has had a greater impact on international flights than on domestic flights, and that the recovery speed of local connectivity has been faster than that of global connectivity (Sun et al., 2020, 2021b; Li et al., 2021; Zhang et al., 2022). For example, researchers studying Incheon International Airport discovered that although the airport's efficiency decreased during the pandemic, the increase in connectivity between Incheon and other airports could improve the airport's efficiency (Shamohammadi et al., 2022).

Some studies have shed light on the heterogeneous impact of the pandemic on different types of airports, including hub and non-hub airports. For example, Mueller (2022) found that non-hub airports in Europe experienced more negative impacts than hub airports. Airports primarily served by LCCs were more likely to be cut off from the network during extensive network shrinkage than those served by FSCs. Other studies have examined the heterogeneous impacts of the pandemic across different regions and countries. Sun et al. (2020) reported that Europe has undergone more significant changes in network connectivity than North America. Many countries in North America, such as the United States, Canada, and Mexico, remained highly connected with other countries during the pandemic. Sun et al. (2021b) also found that, compared to other countries, the impact of the pandemic on airports in the United States was relatively homogeneous, with most airports only partially affected. Although there have been many studies that have explored the impacts of the pandemic on airports from different aspects, there are still no studies dedicated to examining the impact on MASs. For the characteristics of MASs, this study aims to investigate this topic to fill this research gap.

2.2.4 Data and MAS Samples

An MAS is defined as a set of two or more commercial airports that serve air traffic within a metropolitan region (Bonnefoy et al., 2010), regardless of the ownership or political control of individual airports (Wang et al., 2009). In this study, we adopt the definition of Bonnefoy et al. (2010) to select sample MASs. Bonnefoy et al. (2010) used worldwide airport passenger traffic data from the International Civil Aviation Organization (ICAO) (2008) and the Federal Aviation Administration (2007), including all airports with more than 500,000 passengers in 2005. A geographical cluster analysis was conducted to identify MASs. To identify all airports located within a 60-mile radius of the city centre, clusters of two or more significant airports within 120 miles of each other were first identified. Then, certain MASs were excluded based on geographical characteristics, such as the presence of islands and the criterion that the largest airport served fewer than two million passengers per year. Sun et al. (2017) also defined major commercial airports as those with at least two million passengers per year. Based on this analysis, they identified 59 MASs, which was updated to 60 in 2011 (de Neufville, 2016). In our study, we use the MASs list identified by Bonnefoy et al. (2010).

We retrieved our airline scheduled seat data from the Official Airline Guide (OAG) for the sampled MASs as identified in Bonnefoy et al. (2010). These data include departure and arrival airports and airline-specific scheduled seats on a quarterly basis for the 149 airports in the 60 sample MASs from Q1 2018 to Q4 2022, covering both the pre-pandemic and the pandemic periods. The OAG database also includes variables indicating whether a route is domestic or international, and whether an operating airline is an FSC or an LCC. However, during our study period, one airport in each of the Belo Horizonte, Gothenburg, Tel Aviv, and Berlin MASs closed, leading us to exclude these four systems. Additionally, Beijing was included in the MAS list by Bonnefoy (2010), since the city was served by two airports, Beijing Capital Airport and Nanyuan Airport. However, Nanyuan Airport serves only regional routes out of Beijing under special approval granted to selected airlines only and ceased passenger services in 2019. Therefore, we also excluded Beijing from our sample.[19] Similarly, Lübeck Airport in the Hamburg MAS, Forli Airport in the Bologna MAS only serve a limited number of regional routes before the pandemic, leading us to exclude Hamburg and Bologna as well. Other well-known MAS, such as Chengdu (Tianfu and Shuangliu) is not included in the analysis because Tianfu Airport opened in 2021 and pre-pandemic data are unavailable. In the end, we identified a total of 53 MAS in 24 countries for study, as shown in Table 2.2.3.

Table 2.2.3 Sample MASs in this study

Region	MAS | Country	Airports	MAS | Country	Airports
Asia-Pacific	Melbourne | Australia	Melbourne, Avalon	Hong Kong | China	Hong Kong, Shenzhen
	Shanghai | China	Pudong, Hongqiao	Taipei | China	Taoyuan, Songshan
	Osaka | Japan	Kansai, Itami, Kobe	Tokyo | Japan	Haneda, Narita
	Seoul | Korea	Incheon, Gimpo	Bangkok | Thailand	Suvarnabhumi, Don Mueang
Europe	Brussels | Belgium	Brussels, S. Charleroi, Liege	Paris | France	de Gaulle, Orly, Beauvais-Tille, Chalons-Vatry,
	Dusseldorf | Germany	Duesseldorf, Cologne-Bonn, Dortmund, Weeze	Frankfurt | Germany	Frankfurt, Hahn
	Stuttgart | Germany	Stuttgart, Baden	Milan | Italy	Malpensa, Bergamo, Linate
	Pisa | Italy	Pisa, Florence	Rome | Italy	Fiumicino, Ciampino
	Venice | Italy	Marco Polo, Treviso	Amsterdam | Netherlands	Amsterdam, Eindhoven, Rotterdam
	Oslo | Norway	Gardermoen, Sandefjord-Torp	Moscow | Russian	Sheremetyevo, Domodedovo, Vnukovo
	Vienna | Slovakia	Vienna, Bratislava	Barcelona | Spain	Barcelona, Girona, Reus
	Copenhagen | Sweden	Copenhagen, Malmo	Stockholm | Sweden	Arlanda, Bromma, Skavsta
	Istanbul | Turkiye	Istanbul, Sabiha Gokcen	Belfast | UK	Belfast, George Best
	Glasgow | UK	Edinburgh, Glasgow, Prestwick	London | UK	Heathrow, Gatwick, Stansted, Luton, London City
	Manchester | UK	Manchester, Liverpool, Leeds Bradford		

[19] Furthermore, Beijing Daxing Airport had only opened before the pandemic and had limited passenger traffic during the pandemic.

Latin America & Middle East	Buenos | Argentina	Newbery, Ministro Pistarini	Rio de Janeiro | Brazil	Rio de Janeiro, Santos Dumont
	Sao Paulo | Brazil	Guarulhos, Congonhas, Campinas	Tehran | Iran	Mehrabad, Khomeini
	Mexico City | Mexico	Mexico City, Toluca	Dubai | UAE	Dubai, Sharjah
North America	Toronto | Canada	Pearson, Billy Bishop, Hamilton	Vancouver | Canada	Vancouver, Abbotsford
	San Diego | US	San Diego, Tijuana	Boston | US	Logan, Providence, Manchester-Boston
	Chicago | US	O'Hare, Midway, Rockford	Cleveland | US	Hopkins, Akron
	Dallas | US	Dallas, Love Field	Detroit | US	Metropolitan Wayne, Flint
	Houston | US	George Bush, Hobby	Los Angeles | US	Los Angeles, Santa Ana, Burbank, Ontario, Long Beach
	Miami | US	Miami, Lauderdale	New York | US	Kennedy, Liberty, LaGuardia, Islip
	Norfolk | US	Norfolk, Williamsburg	Orlando | US	Orlando, Sanford
	Philadelphia | US	Philadelphia, Atlantic City	San Francisco | US	San Francisco, San Jose, Oakland
	Tampa | US	Tampa, St Pete-Clearwater, Sarasota	Washington | US	Baltimore, Dulles, Reagan

2.2.5 Statistics and Discussions

In this section, we calculate and discuss some statistics and indices to shed light on the impact of the pandemic on MASs worldwide. For concise discussions and clear insights, we concentrate on the major MASs in each region (i.e., North America, Europe and Asia Pacific) while reporting the statistics of all sample MASs in the Appendix B.

2.2.5.1 Traffic and network size distribution within MAS

Individual airports within an MAS may focus on different markets or be served by different types of airlines. For example, FSCs may utilize hub airports to develop extensive regional and inter-continental networks that enable them to leverage various cost and competitive advantages (Zhang 1996; Tu et al, 2020), whereas secondary airports may focus on regional destinations and serve many LCC flights (Wang et al. 2020c). Airlines' frequency choices depend significantly on traffic volume and slot availability, which in term further affect service equality and passenger demand (Wang et al. 2014). The pandemic cause significant yet non-uniform demand reduction, which are likely to have imposed heterogeneous impacts on different airports. To capture the degree of possible uneven or unequal distributions among various entities, we adopt the Gini index as a commonly used measure. We calculate the Gini index of traffic and degree centrality for the sampled MASs before and during the late stage of the pandemic, based on data from Q3 2019 and 2022. The degree centrality is defined as the total number of destinations linked with each airport via direct flights, and it helps to measure the network scope of a particular airport. The Gini index is calculated using the following equation, which measures the degree of inequality in the distribution of airport traffic within the same MAS.

$$G_M = \frac{\sum_{i=1}^{m} \sum_{j=1}^{m} \left| Y_{it} - Y_{jt} \right|}{2m^2 \overline{Y_m}} \tag{2.2.1}$$

where Y_i is the degree centrality or scheduled seats of airport i, and m is the number of airports in one MAS. The Gini coefficient is G_M and it can theoretically range from 0 (complete equality) to 1 (complete inequality). The larger that the coefficient is, the more unequal that the distribution of airport seats is within the MAS.

Tables 2.2.4 and 2.2.5 present the Gini indices of the degree centrality and traffic volume (measured by scheduled seats) for the top 10 MASs in the world, respectively. In the case of London, where international services control a lion's share of the market, our analysis primarily reflect the dynamics of its international market. The Gini indices of both degree centrality and traffic remained relatively stable before (Q3 2019) and during the pandemic (Q3 2022), mainly due to the lifting of travel bans across European countries (and North America) during 2022, which led to a recovery in the intra-European and cross-Atlantic markets. The Gini indices of the degree of centrality and traffic in major US MASs, including New York, Los Angeles, and Chicago, as of Q3 2022, did not change significantly compared with those in Q3 2019. This finding demonstrates that the network and traffic distributions of US MASs were relatively stable once the pandemic was contained and travel restrictions were lifted. This pattern also applies to MASs in Paris. However, for Istanbul, we observe a more unevenly distributed degree of centrality in the domestic market during the pandemic. Istanbul Ataturk Airport is the primary airport in this MAS, focusing on both international and domestic markets, while Sabiha Gokcen

Airport mainly serves the domestic market through LCC services. Prior to the pandemic, 55% of domestic traffic was served by Sabiha Airport. However, with the pandemic's impact, Sabiha Gokcen Airport withdrew some domestic routes, resulting in a decrease in domestic traffic to a level close to that of Ataturk Airport.

Conversely, the MASs in Asia have experienced significant changes in the Gini indices of degree centrality and traffic before and during the late stage of the pandemic. In the case of the Tokyo MAS, Tokyo Narita Airport primarily serves the international market, accounting for 67% of international traffic as of Q3 2019. Haneda Airport, in contrast, focuses mainly on the domestic market, serving 90% of domestic traffic in the same period. Japan adopted stricter travel bans than European and North American countries, with Narita Airport being affected particularly strongly, resulting in a significant decrease in its international degree centrality, from 120 in 2019 to 71 in 2022. Consequently, the difference in international degree centrality between Narita and Haneda decreased during the pandemic, leading to a 25% decrease in the Gini index of degree centrality in the international market. Although the number of international routes from Narita decreased significantly, the airport's dominance in the international market led to an increase in the proportion of international traffic served, resulting in a 10% increase in the Gini index of traffic. Such findings are consistent with the empirical evidence of Ng et al. (2022), who indicated that the Japanese airline market was heavily affected by the pandemic, with the two dominant airlines (All Nippon Airways and Japanese Airlines) strengthening their competition in the major domestic routes linking to Haneda and Narita airports.

In the case of Shanghai, both Pudong and Hongqiao airports serve a considerable number of domestic destinations. However, Hongqiao Airport serves only a small number of international destinations, mainly short-haul flights to Japan and Southeast Asia, while almost all international flights are served by Pudong Airport. During the pandemic, Pudong Airport had more under-utilized slots due to China's implementation of strict bans on international airline services. As a result, Pudong added flights to more domestic destinations, further exceeding Hongqiao in degree centrality in the domestic market. Since Hongqiao previously dominated the domestic traffic volume, the rise of Pudong Airport in domestic services narrowed the domestic traffic imbalance during the pandemic, leading to a 58% reduction in the Gini index of domestic traffic. For Hong Kong, the Chinese government banned flights between Hong Kong and mainland China, resulting in a significant drop in the number of domestic routes and traffic at Hong Kong Airport, increasing the Gini indices of domestic degree centrality and traffic of the MAS by 63% and 75%, respectively. Shenzhen cut almost all international flights during the pandemic, while Hong Kong maintained more international flight services, further exacerbating the uneven distribution of international air services in this MAS.

The Gini indices of degree centrality and traffic for the other sampled MASs are compiled in Appendix Tables B1 and B2, respectively. Overall, the observations indicate that, for European and US airports, the overall inequality of traffic and degree centrality did not change significantly by the end of 2022 compared to pre-pandemic conditions, because domestic traffic and international traffic volumes recovered in a similar pattern. In contrast, for the Asian Pacific MASs, the stricter international air travel bans adopted by these countries were more strict and lasted for much longer periods, which led to a significant redistribution of traffic and networks in the international markets. As airports with more idle slots from international operations switched to domestic flight services, the intra-MAS distribution of domestic operations also underwent significant changes.

Table 2.2.4 Gini index of the degree centrality before (Q3 2019) and during late stage of pandemic (Q3 2022) for top 10 MASs

			Domestic routes			International routes		
Rank	MAS	Region	Before	Late stage	Diff%	Befor e	Late stage	Diff%
1	London	Europe	0.105	0.17	61%	0.211	0.236	12%
2	New York	North America	0.28	0.252	-10%	0.524	0.524	0%
3	Tokyo	Asia-Pacific	0.181	0.204	13%	0.279	0.21	-25%
4	Hong Kong*	Asia-Pacific	0.227	0.371	63%	0.174	0.3	72%
5	Shanghai	Asia-Pacific	0.131	0.198	51%	0.457	0.5	10%
6	Paris	Europe	0.5	0.47	-6%	0.497	0.426	-14%
7	Los Angeles	North America	0.39	0.326	-16%	0.771	0.708	-8%
8	Istanbul	Europe	0.049	0.063	28%	0.247	0.248	0%
9	Chicago	North America	0.459	0.438	-5%	0.573	0.55	-4%
10	Bangkok	Asia-Pacific	0.141	0.119	-16%	0.167	0.223	34%

Notes:
1. The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2. The rank of the airports is defined by the total scheduled seats of the MAS at Q3, 2019.
3. A smaller Gini index indicates a more balanced distribution of degree centrality.
4. *The Hong Kong MAS includes the airports in the two nearby cities of Hong Kong and Shenzhen.

Table 2.2.5 Gini index of the traffic (scheduled seats) before (Q3 2019) and during late stage of the pandemic (Q3 2022) for top 10 MASs

			Domestic			International		
Rank	MAS	Region	Before	Late stage	Diff%	Before	Late stage	Diff%
1	London	Europe	0.326	0.31	-5%	0.406	0.402	-1%
2	New York	North America	0.259	0.252	-3%	0.568	0.564	-1%
3	Tokyo	Asia-Pacific	0.399	0.387	-3%	0.173	0.191	10%
4	Hong Kong	Asia-Pacific	0.257	0.449	75%	0.403	0.469	16%
5	Shanghai	Asia-Pacific	0.025	0.01	-58%	0.422	0.5	19%
6	Paris	Europe	0.543	0.513	-5%	0.594	0.541	-9%
7	Los Angeles	North America	0.543	0.491	-9%	0.791	0.782	-1%
8	Istanbul	Europe	0.055	0.028	-49%	0.286	0.265	-8%
9	Chicago	North America	0.513	0.474	-8%	0.636	0.626	-1%
10	Bangkok	Asia-Pacific	0.158	0.043	-73%	0.238	0.37	56%

Notes:
1. The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.
3. A lower Gini coefficient value reflects a more equitable distribution of traffic volumes among airports in the MAS.

2.2.5.2 Intra-MAS airport competition and market overlap

In this subsection, we focus on the origin-destination (OD) level competition among different airports within one MAS. That is, the different airports in one MAS might offer direct flights to the same destination. The intra-MAS airport competition is fiercer when airports serve more overlapping destination markets. To more accurately capture such intra-MAS competition (degree of market overlap), we devise with the following Herfindahl-Hirschman (HHI) index on each route originating from one MAS.

$$OD\_HHI_{Mj} = \sum_{i=1}^{m} \left(\frac{q_{ij}}{Q_{Mj}}\right)^2 \tag{2.2.2}$$

where Q_{Mj} is the total scheduled seats from MAS M to destination airport j; q_{ij} is the scheduled seats from airport i in the MAS to destination airport j; and m is the number of airports in MAS M. Then, for each sample MAS, we are able to calculate this HHI index for each OD market. A larger value of HHI suggests higher market concentration, or more dominance of the leading airport(s) within the MAS serving this OD market.

For our empirical investigation, we focus on the top 5 MASs worldwide, namely London, New York, Tokyo, Hong Kong, and Shanghai. These MASs are distributed in major regions around the world. In the following figures, we present the percentage distributions of the OD level HHIs, as calculated in Eq. (2.2.2). For the London MAS, the HHI index became more concentrated towards lower values, indicating more intense competition among different airports in the London MAS. As we discuss in more detail in the next subsection, British Airways dominated at London Heathrow Airport, while LCC EasyJet operated its base airport at London Gatwick Airport. During the pandemic, British Airways relocated its capacity from intercontinental routes to more intra-European routes at its Heathrow hub, leading to more head-to-head competition with EasyJet at London Gatwick. For the New York MAS, there was no significant change in the OD level HHI during the pandemic. This outcome can be attributed to the almost full recovery of the US aviation market in Q3 2022 compared with Q3 2019, with airlines returning service levels and network configurations to pre-pandemic levels. In other words, we did not observe any clear or long-term changes in the MAS structure caused by the pandemic in the US.

In the case of the Tokyo MAS, the intra-MAS competition between Narita and Haneda airports appeared to intensify, with an overall decrease in the OD level HHI. This result occurred primarily because, during the pandemic, both airports cut services in thin markets and focused on denser and more lucrative routes, enhancing their market overlap and head-to-head competition. For the Hong Kong MAS, both the Hong Kong and Shenzhen airports were heavily impacted during the pandemic. Before the pandemic, they served many common destinations in mainland China, as well as short- to medium-haul international routes. However, most of the flights from Hong Kong to mainland Chinese cities were suspended during the pandemic, and international flights from Shenzhen were also dramatically reduced. Consequently, the two airports' networks became very distinct during the pandemic. Last, in the case of the Shanghai MAS, the competition between the Hongqiao and Pudong airports became much more intense. As discussed in the previous subsection (2.2.5.1), to alleviate the adverse impact of the pandemic, Pudong Airport expanded its domestic market services, resulting in increased head-to-head competition with Hongqiao Airport in many domestic OD markets.

We also calculated the average OD level HHI for each MAS to provide an overall measure of changes in airport competition within the MAS (as illustrated in Figure 2.2.2). Except for the Hong Kong MAS, all four of the other systems experienced increased intra-MAS airport competition during the later stage of the pandemic, consistent with our earlier analysis.

Furthermore, we compiled the distribution of the OD level HHI and average OD level HHI before and during the late stage of the pandemic for other sampled MASs and we present the results for the top 30 MASs in Figures B1 and B2. Overall, the observations indicate that for US and European MASs, once travel bans were lifted, the intra-MAS airport competition structure returned to pre-pandemic levels. In contrast, for Asian Pacific MASs, intra-MAS airport competition could be significantly reshaped because relevant airports' operations had been significantly constrained by strict international air travel bans.

Fig. 2.2.1: The distribution of OD HHI for top 5 MAS before (Q3 2019) and during late stage of pandemic (Q3 2022)

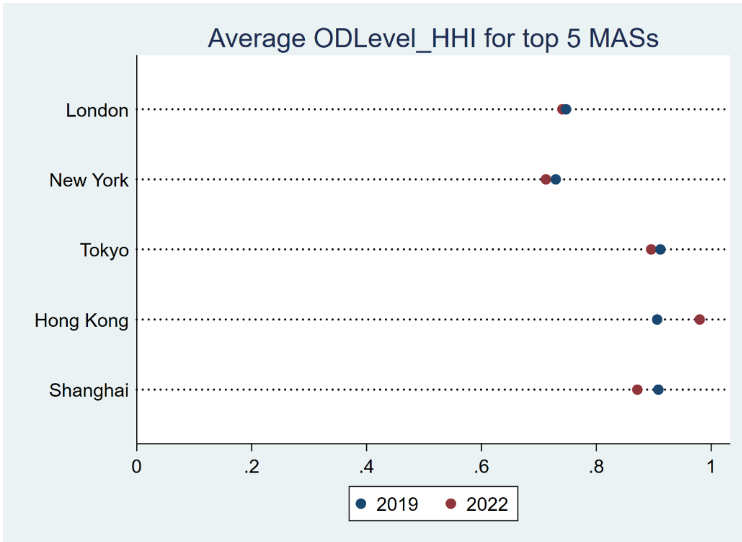


Fig. 2.2.2: The Average OD HHI for top 5 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022)

2.2.5.3 Airline competition within the MAS

In this subsection, we examine the impact of the pandemic on airline-level competition within MASs. First, to measure the overall airline competition intensity, we calculate the airline HHI in each MAS using the following equation.

$$Airline\_HHI_M = \sum_{i=1}^{N} \left(\frac{q_{iM}}{Q_M}\right)^2 \tag{2.2.3}$$

where q_{iM} is the scheduled seats of airline i in MAS M, regardless of airport; Q_M is the total scheduled seats in MAS M; and N is the number of airlines in MAS M. A larger value of airline HHI suggests more dominance of particular airlines within one MAS. Table 2.2.6 summarizes the airline HHIs for the top 10 MASs before and during the late stage of the pandemic. For US and European MASs, the airline HHI did not change significantly. This outcome suggests that there were no significant airline exits in these MASs during the pandemic. While some airlines might have exited the market in the early stages of the pandemic, once it was under control and most travel bans were lifted, airline services resumed quickly, leading to similar airline concentration levels. In contrast, for Asia-Pacific MASs, the concentration level of airlines increased significantly, with some airlines becoming much more dominant during the pandemic. One possible explanation is the crowding effect imposed by large-sized dominant airlines. Since international flight services were largely suspended, airlines that previously served international markets redeployed their capacity in domestic markets, intensifying competition and leading to exits of small airlines and LCCs. The MASs thus became more concentrated. We also compiled the airline HHI results for other MASs in Appendix Table B3. Notably, for small-scale MASs, such as Milan and Venice, their airline HHIs also increased significantly due to economies of scale. With air traffic dropping during the pandemic, it was difficult for all airlines to achieve efficient operations, and some inefficient airlines exited the market, leading to a higher airline HHI. The results from Chapter 2.1, which indicate intensified competition between LCC and FSCs on dense routes, do not contradict the findings from this chapter, which reveal less intense airline competition among airports within the MAS. The first reason for this is that the first study is conducted within the Chinese market and focuses on airline competition at the route level, while the second study examines competition among airports at the global MAS level. Additionally, the first study only investigates the competition between LCCs and FSCs, without considering the competition among FSCs themselves.

Table 2.2.6 Airline HHI of top 10 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022)

Rank	MAS	Before	Late stage	Diff%
1	London	0.118	0.115	-3%
2	New York	0.139	0.151	9%
3	Tokyo	0.183	0.235	28%
4	Hong Kong	0.079	0.123	55%
5	Shanghai	0.125	0.155	24%
6	Paris	0.176	0.177	0%
7	Los Angeles	0.118	0.124	5%
8	Istanbul	0.456	0.486	6%
9	Chicago	0.238	0.234	-2%
10	Bangkok	0.080	0.080	0%

Notes:
1. The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.
3. The declining airline HHI values reflect intensified competition among airlines in the MAS.

In addition to overall airline concentration, we also investigated competition between FSCs and LCCs in MASs. In some MASs, FSCs and LCCs prefer to have hubs at different airports. For example, in the London MAS, British Airways (FSC) has its hub at Heathrow Airport, while EasyJet has its main base at Gatwick Airport. In other MASs, FSCs and LCCs are not clearly distinguished in hub airports. For instance, in the Shanghai MAS, Spring Airlines (a LCC) and China Eastern Airlines (a FSC) claim hubs at both Hongqiao and Pudong airports. Spring Airlines aims to enter both airports to attract passengers with different airport preferences in the MAS, but doing so could hinder their achievement of economies of scale. The pandemic might have affected the incentives of FSCs and LCCs to choose airport entry and capacity distribution in the MAS. Thus, we calculated the Gini index of LCC capacity share, and the results for the top 10 MASs are shown in Table 2.2.7. First, for European and US MASs, the LCC capacity share became slightly more balanced during the pandemic, as indicated by an overall decrease in the Gini index. This outcome suggests that LCCs preferred to maintain the presence at multiple airports in MASs to serve passengers that have different airport preferences. This is probably due to LCCs' significant market shares and traffic volumes, which enable them to maintain sizeable operations at multiple airports. This is helped by the fact that LCCs offer simplified services (e.g. no connection nor complicated baggage handling, simple catering services), thus not too costly to maintain operations at multiple airports.

However, for Asia-Pacific MASs, particularly the Shanghai MAS, LCCs preferred to concentrate operations in a single airport, Pudong Airport, during the pandemic. There are two possible rationales for this choice. First, LCCs have a much smaller presence and market occupation in China and Japan, especially in China (no more than 15%). Therefore, it is crucial for them to have sufficient traffic to achieve economies of scale, especially when many input prices are beyond the control of LCCs (Fu et al. 2015; Su et al. 2020). When the market is in a downturn and the traffic volume is low, LCCs must consolidate traffic into one airport in the MAS to maintain a certain level of operational scale. Our data show that China's largest LCC, Spring Airlines, increased its market share at Pudong Airport more than at Hongqiao Airport during the pandemic. When more idle slots are available for redistribution, LCCs can acquire them and expand services, in line with China's policy allowing LCCs to obtain new slots and open new routes from major hub airports (Shanghai and Beijing) during the pandemic as an indirect measure to support private LCCs in surviving the market downturn (e.g., Hou et al., 2021). Second, FSCs in the Asia-Pacific region faced more restrictive bans on operating international markets, forcing them to compete more aggressively in the domestic market to survive. They attempted to prevent LCC expansion in their hub airports by adopting more aggressive competition strategies, such as deep price discounts. The Gini index of LCC capacity share for other MASs is available in Appendix Table B4.

Table 2.2.7 Gini index of LCC capacity share in top 10 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022)

Rank	MAS	Before	Late Stage
1	London	0.461	0.437
2	New York	0.428	0.379
3	Tokyo	0.269	0.332
4	Hong Kong	0.148	0.190
5	Shanghai	0.026	0.069
6	Paris	0.321	0.290
7	Los Angeles	0.247	0.209
8	Istanbul	0.467	0.489
9	Chicago	0.309	0.296
10	Bangkok	0.385	0.282

Notes:
1. The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.
3. A lower Gini coefficient indicates a more equitable distribution of LCC seat capacity among MAS airports.

2.2.6 Summary

This study first reviewed and summarized the recent literature on MASs, discussing the main research topics and development patterns. It is noted that the impacts of the pandemic on MASs have not been well explored in the literature. Therefore, we collected airport-airline-specific capacity data from OAG (before and during the late stage of the pandemic) to examine the pandemic’s impact on different dimensions of MAS operations worldwide following the definitions used in previous studies for consistency. A total of 54 MASs are included in our sample, with a focus on the top MASs around the world. By calculating descriptive statistics and indices, we studied three dimensions of MAS structures before and during the late stage of the pandemic: i) traffic and degree centrality distributions within MASs; ii) intra-MAS airport competition (the degree of OD market overlap); and iii) airline competition intensity within MASs.

The statistics suggest heterogeneous impacts of the pandemic on MASs in different regions when comparing market outcomes between Q3 2019 (before the pandemic) and Q3 2022 (during the pandemic). For MASs in the US and Europe, the distribution of traffic and degree centrality among airports remained largely unchanged. Both the domestic and international airline markets in these MASs have returned to pre-pandemic levels at similar paces. Until the end of 2022, intra-MAS airport competition and airline airport dominance and concentration (including between FSCs and LCCs) have also been similar to pre-pandemic levels at major European and US MASs. These results suggest the stability of MAS structures in the US and Europe after their airline markets recovered from the unprecedented shock of the pandemic.

In contrast, Asia-Pacific MASs experienced significant changes during the pandemic, mainly due to very restrictive bans on international travel. Since large-sized airlines could not serve international markets, they had to redeploy their capacity into domestic markets, leading to significant changes in the MAS structure. First, airport traffic could be more balanced within the MAS, and intra-MAS airport competition became much fiercer as airports focused on operations in similar domestic destinations. On the other hand, smaller airlines dropped quite a few markets, leading to higher airline concentration levels. The net effect (i.e. whether competition in an MAS increased and decreased) remains unclear. It is also noted that LCCs in Asia-Pacific seemed more likely to have a main base in a single airport in one MAS, either due to the incentive of achieving economies of scale or they were pushed out from other airports due to stronger competitive responses from FSCs who were forced to allocate more capacity to domestic markets.

In general, this study identified heterogenous development and recovery patterns among MASs in different regions. Although some possible explanations are proposed, more in-depth analysis is required to go beyond simple statistics. This study also raised some questions unanswered. For example, government interventions in the European and North American markets, where market largely returned to pre-pandemic conditions, are probably not necessary. Yet it is not clear whether the any government intervention should be considered to address the heterogenous impacts caused by the pandemic, especially for “distortions” caused by previous regulations (e.g. ban on international services). Future research could identify and estimate the impact of various government policies at different stages of the pandemic on changes in MAS competition. The definition of MAS could affect the results. A more lenient distance restriction for identifying MAS could encompass more airports, such as including Zhuhai and Macau airports within the Hong Kong MAS. Future studies could identify the impact of the pandemic on MAS operations based on a broader definition of MAS and compare these findings with the conclusions of this study. Extension studies based on updated data can be helpful in addressing those important questions.

CHAPTER 3.

IMPACT OF AIR CONNECTIVITY ON BILATERAL SERVICE EXPORT AND IMPORT TRADE

CHAPTER 3: PREFACE

In the following chapter, I use empirical models to investigate the social benefits of air connectivity from the perspective of service trade. This chapter will first examine the impact of air connectivity on China's bilateral service trade, then analyze the effects of open skies air services agreements (OSAs) on bilateral service trade using data from the United States. We focus on these two countries for several reasons. China is the second-largest country in terms of service trade, and its international air transport has experienced tremendous growth and significant reforms over the past two decades. Exploring the relationship between China's aviation development and service trade can provide valuable insights for developing countries. The United States, on the other hand, is the most active country in promoting the signing of OSAs; as of 2023, it has signed OSAs with 135 partner countries and regions. In this context, we investigate how the signing of OSAs facilitates service trade, along with its lead and lag effects.

The study presented in section 3.1 has been published verbatim under the title "Impact of Air Connectivity on Bilateral Service Export and Import Trade: The Case of China" in *Transport Policy* (Oum et al., 2024), with minor edits made to adapt the formatting to match other chapters. Although in this study, I am the second and corresponding author. I was primarily responsible for conducting all empirical analyses (including data processing and the instrumental variable estimation) and drafting the initial manuscript. My co-authors contributed through theoretical guidance, policy interpretation, and manuscript refinement. The study in section 3.2 is a working paper. In this study, I take the lead in developing the empirical model, interpreting the results, and drafting the manuscript, while acknowledging the valuable contributions of my co-authors in providing guidance, and revising the paper.

3.1 The Case of China

3.1.1 Abstract

This study examines the effect of bilateral air connectivity on bilateral service trade flows. Service trade data includes ‘commercial’, ‘transport’, ‘travel’, and ‘government’ services. We developed a reduced-form gravity-type model using the Chinese data. The reduced-form model offers greater flexibility and requires fewer assumptions, making it easier to estimate and interpret. This simplification allows us to focus on the direct effects of air connectivity on trade outcomes without the complexities of underlying structural relationships. An instrument variable (IV) approach is adopted to address the endogeneity issue between bilateral air connectivity and the service trade variables. Our key results are: (a) increasing the number of direct routes can significantly promote bilateral service export and import trades; (b) the average route-level traffic density has only marginal positive effects; (c) improving air connectivity would enlarge China’s overall service trade deficit, because the transport and travel services imports are promoted more than their exports; (d) The ‘commercial’ service exports can be stimulated more than the imports, making China achieve larger commercial service trade surplus by improving bilateral air connectivity.

3.1.2 Introduction

While the impact of transport costs and connectivity on merchandise trade flow has been heavily researched, our study investigates the effect of air connectivity on service trade. Service trade is often categorized as commercial, travel, transport, and government services (see UN Comtrade Table C1 in Appendix). While some of these services are conducted virtually online, much of the service trades are done by on-site professionals. Many service export and import trades need face-to-face communications and/or meetings since it is an essential element for exploring potential business and collaborative opportunities (Poole, 2010; Cristea, 2011; Belenkiy and Riker, 2012). According to Startz (2016), implicit trade barriers can be reduced by traveling abroad and conducting face-to-face meetings. Among different transport modes, the air transport is the most convenient one to facilitate movement of people between countries and to reduce trade costs (Yilmazkuday and Yilmazkuday 2014). Thus, air connectivity between the two countries could play a very important role in stimulating bilateral service trade. China has the second largest air transport market in the world[20], and its service trade sector and international airline market are fast growing. Therefore, it gives us an ideal framework to study the impact of international air connectivity on service trade.

Figure 3.1.1 shows that service trade in China has been growing faster than the merchandize trade. While China has maintained a service trade deficit with the world, especially with the US, it has a significant merchandise trade surplus over the years. For example, from 2014 to 2019, China's service trade grew at an average annual rate of 7.8 percent, 2.2 times of the growth rate of the merchandize trade. Furthermore, in order to better integrate with the global economy, China has also launched stronger measures to open up its service trade markets. For instance, since the year 2019, China has held the China International Import Expositions. Also, several Chinese cities were designated as pilot cities to implement free trade zones for service sectors to attract foreign direct investments (FDI) and sign new service business contracts. The development of Chinese service trade will stimulate cooperation between different countries and regions and serve as an important engine for bilateral and multilateral trade.

China's international air transport has experienced tremendous growth and major reforms over the past two decades. Its international air networks experienced exponential growth since China joined the World Trade Organization (WTO), which increased the demand for international travel. In addition, the Belt-and-Road Initiative (BRI) increased international connections between China and the BRI countries and facilitated China's international air travel to a large extent (Huang and Wang, 2017; Cheung et al., 2020b; Hou et al., 2022b). Also, Chinese citizens go abroad for leisure and education a lot more often thanks to the China's relaxation of international travel and the increased per capita income. These contributed to a rapid growth of China's international aviation market (Dai et al., 2017; Liu et al., 2018). As a result, the number of international airports increased from 22 in 2000 to 76 in 2019, while the number of international air routes increased from 133 in 2000 to 953 in 2019. The number of foreign countries with direct international air travel

[20] According to air transport passenger volume data from the World Bank, China is the second-largest air transport market. Source:
https://data.worldbank.org/indicator/IS.AIR.PSGR?end=2019&most_recent_value_desc=true&start=1970

link with China increased from 33 in 2000 to 65 in 2019, while the number of foreign cities with direct airline service from China increased from 56 in 2000 to 167 in 2019 (CAAC, 2020).

This study empirically examines the effect of the bilateral air connectivity on the bilateral service trade flows with the focus on China. We measure air connectivity by the number of direct routes and air traffic density per route (i.e., the average passenger volume per direct route). This study analyzes the impact of air connectivity on each of the overall service export and import, and the three service trade components, ‘commercial’, ‘travel’, ‘transport’. Figure 3.1.2 shows that ‘commercial’ and ‘travel’ services are the dominant components of China’s service export and import trades. This is sensible as China exports heavily infrastructure construction services as a part of its investments in the BRI countries. In 2020, despite the negative impact of COVID-19 pandemic, China was still able to sign infrastructure construction contracts with 184 countries and regions, at total value of 255 billion RMB (approximately 40 billion USD). Before the pandemic, China’s outbound tourism reached 155 million people, and the number of students studying overseas reached 700 thousand in 2019. In the empirical section, we estimate and analyze the impacts of China’s international air connectivity on their service export and import trades with bilateral trading partners. One major issue to identify the casual inference is the apparent endogeneity issue due to the mutual relationship between the air connectivity and bilateral trade. This study adopts an instrumental variable (IV) approach with an IV by taking mean of the number of foreign cities that have direct flights to China and the number of foreign cities that have direct flights to the service trade partner countries.

The rest of the study is organized as follows. Section 3.1.3 reviews the literature. Section 3.1.4 introduces data sources, variable definitions, and the econometric model specifications as well as explaining the detailed IV approach used. The empirical results are discussed in Section 3.1.5 followed by Section 3.1.6, which concludes this study.

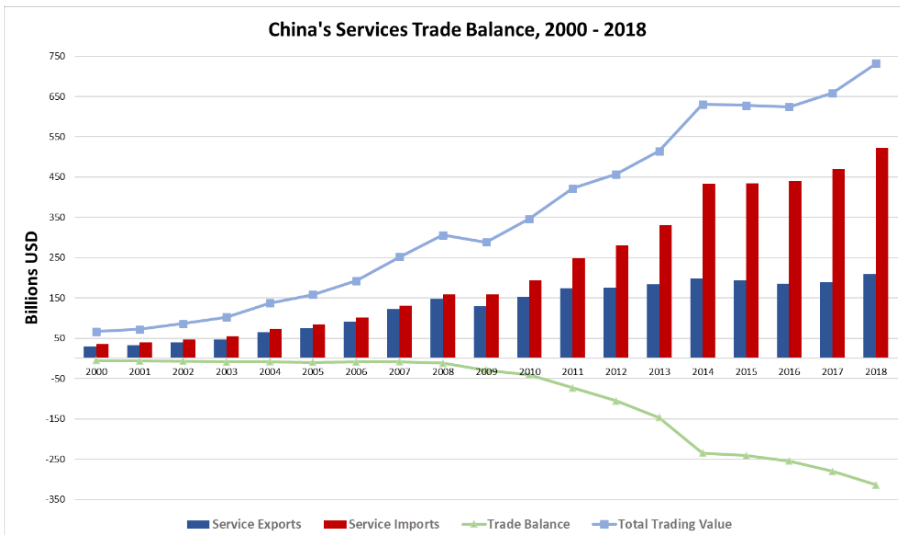
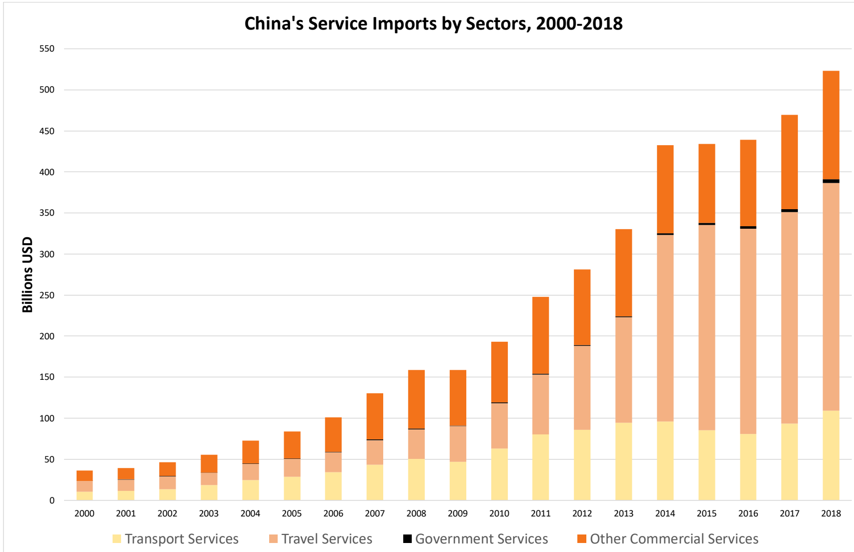


Fig. 3.1.1: China's trade pattern in recent years
Note: Merchandise trade refers to the exchange of goods between countries, which includes tangible products like electronics, clothing, and raw materials.
Source: made by authors with data from UNcomtrade.



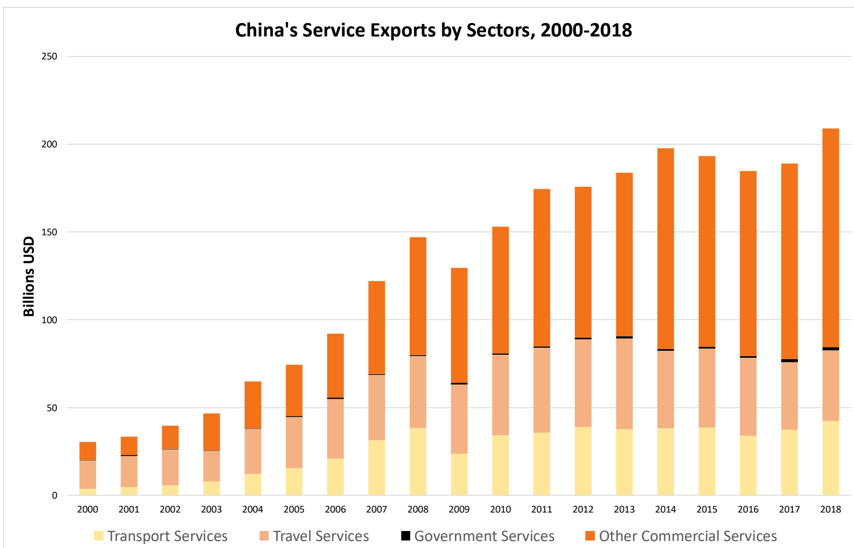


Fig. 3.1.2: China's service imports and exports by sectors
Note: Detailed components of each types of service trade can be found in Table C1.
Source: made by authors with data from UNcomtrade.

3.1.3 Literature Review

This study is related to two streams of literature: the impact of air transport liberalizations on economic growth and the effect of air transport on bilateral trade.

3.1.3.1 Air liberalization and economic growth

This study attempts to contribute to the literature that examines the relationship between air transport liberalization and economic growth. Previous studies have identified that Open Skies Agreements (OSAs) and other liberalized air services agreements have increased flight frequencies and competition, reduced fares, increased passenger volumes and improved welfare and regional economic growth (Dresner and Windle, 1992; Stockfish, 1992; Forsyth, 1998; Clougherty et al., 2001; Gillen et al., 2002; Fu et al., 2010; Huderek-Glapska, 2010; Adler et al., 2014; Abate, 2016; Dobruszkes et al., 2016; Bernardo and Fageda, 2017; Seetanah et al., 2019). Piermartini and Rousova (2013) find that full adoption of OSAs would increase the worldwide passenger traffic by 5%. Furthermore, Winston and Yan (2015) show that OSAs signed between the US and other countries have generated 4 billion USD per year welfare gain to the US international travelers. Gillen and Hinsch (2001) demonstrate the impact of air liberalization on economic growth using the case of Hamburg airport. Gillen, Harris and Oum (2002) construct a model that shows the consequences of liberalized air trade using the case of Canada-Japan market. They find that lifting entry restrictions alone has a limited or no impact on consumer and carriers' welfare, while adding price competition would improve both consumer and carriers' welfare.

Additionally, using difference-in-differences approach, Kneller et al. (2008) analyze the relationship between the trade liberalization and economic growth. They use a five-year average period before, during and after liberalization took place. The authors find that countries that were well-off before liberalization continued this trend after the liberalization. Bannò and Redondi (2014) who studied the relationship between air connectivity and FDI show introducing new routes has a positive impact on FDI. Chen and Lin (2020) also find the increase of direct flights between China and other BRI countries helps raise the cross-border investments. Bilotkach (2015) demonstrates that traffic volume and the number of direct flight destinations have a positive effect on economic development, by increasing income level, employment and businesses.

3.1.3.2 Air connectivity and bilateral trade

This study also attempts to contribute to the research on the impact of air connectivity on bilateral trade. The air liberalization affects international merchandize trade through the deregulation in air cargo services in international markets. Micco and Serebrisky (2006), Endo (2007), and Yamaguchi (2008) find that OSAs have caused a significant decline in the air freight rate, and thus, increases the bilateral freight transport (i.e., the merchandize trade). Similarly, since most service trades require face-to-face interactions, a reduction in travel cost due to air liberalization makes it more convenient and less costly for people to travel and meet in person. Kern et al. (2021) show that a reduction in administrative barriers between European Union (EU) member countries increased an intra-EU trade and contributed to an increase in member countries' welfare between 0.39% and 1.32%. Additionally, Poole (2010) identifies business travel as an essential input to international trade. Startz (2016) finds that business travel for face-to-face meetings is an effective way to ease product searching and contract negotiation. Moreover, Tanaka (2019) finds that the face-to-face interactions via air travel stimulate cross-border manufacturing. Zhang et al. (2017) also show that international air connectivity has a higher positive impact on bilateral trade in the industries where face-to-face interactions are especially important.

Previous studies almost exclusively examine the other determinants on bilateral service trade (e.g.,Ceglowski, 2006; Kimura and Lee, 2006; Guillin, 2013; van der Marel and Shepherd, 2013; Anderson et al., 2014; Christen and Francois, 2015). Oum, Wang, Yan (2019) is the first study to examine how international air liberalization can affect bilateral service trade. They documented Canada's open skies agreement (OSA) policy and investigated how signing of OSAs can increase country's bilateral air traffic volume, and thus, contribute to Canada's service trade growth with the OSA countries. OSAs are found to be the most effective in promoting 'commercial' service export and import trades. However, the study by Oum et al. (2019) does not deal with the impact of air connectivity as it focused on the effects of OSAs on service trade.[21]

Our study further contributes to the literature on bilateral service trade by using China's service trade data to give more insights on the impact of international air transport development on service trade. Chen and Lin (2020) use the total number of direct flights operated between two countries and the number of passengers traveled via those direct flights to measure the air connectivity and study its impact on FDI. Hoffmann et al. (2020) and Saeed et al. (2020) examine the impact of international liner shipping on countries' merchandize trades, using the Liner Shipping Bilateral Connectivity Index (LSBCI) as a

[21] China did not sign many OSAs as Canada did. The country only signed OSAs with South Korea, Japan and 10 ASEAN countries. It is thus not practical to examine the impact of OSA on China's service trade given the very limited number of OSAs signed by China.

measure of liner shipping connectivity. The LSBCI is a well-developed index that counts the number of direct liner shipping routes, scheduled capacity, and the route-level competition (an important factor to determine the freight rate). However, there has been no existing research that studied the impact of international air connectivity on the bilateral service trade. It should also be noted that, although there are a few studies that quantify the air connectivity using complex theoretical framework, their suggested measures are applicable mostly to a one-node airport (e.g., Burghouwt and Redondi, 2013; Zhang et al., 2017; Zhu et al., 2019). In addition, we refer to Chen and Lin (2020) and LSBCI to find a more aggregated measurement to calculate air connectivity between two countries. Therefore, we use the total number of bilateral direct flight routes to measure the scope of the bilateral air connectivity, and the average number of direct flight passengers per route to measure the average density of the air connectivity. Therefore, improvements in bilateral air connectivity can be achieved through the expansion of the network scope and/or route-level passenger density.

3.1.4 Econometric Model and Data Description

3.1.4.1 Basic model specification

Similar to Oum et al. (2019), we adopt a reduced-form gravity-type equation to examine the impact of international air connectivity on bilateral service trade.[22] Our gravity-type regression equation is specified as follows,

$$\ln Y_{it} = \alpha_0 + \alpha_1 \ln Airconnectivity_{it} + BX_{it} + \mu_i + \rho_t + \varepsilon_{it} \tag{3.1.1}$$

where subscript i denotes a service trading partner country and the subscript t denotes the year. The definition of the variables are as follows:

- Y_{it}: log of the service trade value such as service export, import and total value, respectively, as well as three categories of service trade (commercial, transport, and travel);
- $Airconnectivity_{it}$: network scope measured by the log of the total number of direct routes between China and a partner country, or the route-level traffic density calculated by the log of the average passenger number per direct route;
- X_{it}: vector of log of partner's population, GDP, exchange rate, internet penetration

[22] In spirit of the gravity model used in merchandize trade, Walsh (2008) is the first study to adopt the gravity model to examine the determinants of bilateral service trade, and find the model works well.

rate, LSBCI and dummy variables such as Regional Trade Agreement (RTA) status[23];

- μ_i: country fixed effect for each of China's trading partner i;
- ρ_t: time-specific fixed effect;
- ε_{it}: pure random error item.

For the service trade, we choose to study the impact of the bilateral air connectivity on the total bilateral service export and import, and the subcategories of the commercial, travel and transport. Unlike other service trade items, the government service trades (which is typically less than 1% of total service trade) cannot be explained well by the market-driven or trade factors, thus we decided to exclude it from our analysis.

On one hand, the air connectivity between China and the partner country is expected to promote the bilateral service trade. On the other hand, the bilateral service trade may also encourage air connectivity between two countries since the cross-country travels are done mainly via air transport. Therefore, the reverse causality between air connectivity and service trade will lead to the endogeneity issue, which is discussed in the next section.

3.1.4.2 Endogeneity issue

Our baseline gravity-type regression model cannot identify a causal relationship between air connectivity and service trade due to the endogeneity problem. Thus, we adopt an instrumental variable (IV) approach for the model identification. A valid IV needs to satisfy two conditions, namely the relevance and exclusion conditions. The relevance condition asks the IV to directly affect the endogenous variable, while the exclusion condition requires the IV does not directly affect the dependent variable or is correlated with the error term. This suggests that the IV leads to an exogenous variation in the endogenous variable to lead to changes in the dependent variable. In this study, we propose an IV, $Connectivity\_IV_{it}$, for our air connectivity measurements. This IV is calculated by taking the average of two components: the number of foreign cities that have direct flights to China and the number of foreign cities that have direct flights to the partner country. The

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[23] Travel bans and tariffs between countries can influence service trade. These effects can be moderated by the key independent variable, air connectivity, where smaller seat capacities indicate stricter travel bans. Tariffs can be partially controlled by Regional Trade Agreements.

IV excludes the direct flight routes between China and the particular trading partner country under consideration. The rationales for the validity of this IV are as follows: a larger value of $Connectivity\_IV_{it}$ suggests that China or the foreign trading partner country have a higher degree of air connectivity via other countries around the world. This may suggest that China or the trading partner country developed:

1. Sufficient global air connectivity with own competitive international carriers,
2. Larger international air travel demand that reflects its globally well integrated economy, and/or
3. More liberalized international air policies.

Thus, it is sensible to believe that the air connectivity is also more likely to be better developed between China and the particular trading partner country if the value of $Connectivity\_IV_{it}$ is large. Thus, the relevance restriction is satisfied for this IV. Moreover, $Connectivity\_IV_{it}$ variable is exogenous from the air connectivity between these two countries since it excludes the direct flight routes between China and the particular trading partner country under consideration. Therefore, the exclusion assumption also holds for this IV.

Our selection of IV is inspired by Winston and Yan (2015). They found an IV for the OSAs signing between countries such as they count the number of OSAs a particular bilateral partner country signed with other countries in order to measure how active or liberalized international air policy is in that country. According to Winston and Yan (2015), two countries are more likely to sign an OSA if they already signed more OSAs with other countries. Therefore, one alternative IV we could consider is the mean of China's and a trading partner's average passenger number per direct route with other countries in the world. However, our simple correlation test demonstrates a positive correlation of approximately 0.7 between $Connectivity\_IV_{it}$ and this alternative IV. Thus, because of the potential multicollinearity issue we decided to use $Connectivity\_IV_{it}$ as our instrumental variable.

A two-stage regression is estimated to study the impact of air connectivity on a bilateral service trade. The first-stage regression equation is specified as follows,

$$\ln Airconnectivity_{it} = \beta_0 + \beta_1 \ln Connectivity\_IV_{it} + GX_{it} + \nu_i + \eta_t + \xi_{it} \tag{3.1.2}$$

The second-stage regression equation is specified as follows,

$$\ln Y_{it} = \alpha_0 + \alpha_1 \ln \widehat{Airconnectivity}_{it} + BX_{it} + \mu_i + \rho_t + \varepsilon_{it} \tag{3.1.3}$$

Equation (3.1.3) identifies the effect of air connectivity on China's bilateral service trade with a consistent estimator of α_1. The exogenous variables X_{it} are also included in the first-stage and the second-stage regressions along with the time and country-pair fixed effects.

3.1.4.3 The data

Our main goal is to investigate the impact of the international air connectivity on the bilateral service trade of China. The United Nation (UN) service trade database is the main source of China's bilateral service trade data. The database contains China's annual service trade data with each of 45 partner countries for the period from 2005 to 2018. The service trade data is categorized into four types, namely the commercial, travel, transport, and government as explained in the Appendix Table C1. The estimation is conducted on the subcategories, commercial, travel, and transport, respectively.

To construct the air connectivity variables, we use the data from the IATA PaxIS database, including the direct flight operation data and the passenger volume data for the 2005-2018 period. The database contains the route-specific passenger volume of the direct flights between China and other countries. The number of routes with direct flights measures the network scope of the bilateral international airline network between China and the trading partner. While the average number of passengers per route traveled on direct flights measures the density of traffic flow given the fixed network size.

Figures 3.1.3 and 3.1.4 summarize China's overall air connectivity with sampled trading partners measured by the two variables as discussed in the last paragraph. Figure 3.1.3 demonstrates an upward trend in the number of the direct routes during our sample period. It declined significantly in the year 2009 due to the negative impact of the Global Financial Crisis and then recovered in the year 2010. The number dropped slightly in years 2017 and 2018 due to the China–United States trade war. Unlike Figure 3.1.3, the average route-level traffic density does not have a clear pattern (as shown in Figure 3.1.4). It shows an increase in the number of passengers during the Global Financial Crisis in 2009 and 2010 due to the decline in the number of thin routes and keeping the important trunk routes in the network. As a result, the average route-level traffic density increased. The average passenger number per route has declined since 2001 and then maintained its level despite the growing number of direct routes, suggesting the newly added routes are relatively thin routes.

Table 3.1.1 shows summary statistics of the main variables used in the econometric estimations. As shown in Table 3.1.1, the average dollar amount of service export between China and 45 partner countries is 1.7 billion USD, while the average dollar amount of service import is 3.1 billion USD. China incurs an overall service trade deficit with these trading partners. The average number of bilateral direct flight routes between China and other countries is 9.5. The average number of the direct flight passengers per route is 21 thousand per year. Also, the average internet penetration rate is 50% of the population, which is calculated as the percentage of the population that uses the internet. Moreover, we include the exchange rate variable that measures China's exchange rate fluctuations, which may affect bilateral trade. It is measured as the amount of foreign currency per RMB, using 2005 as the base period.

LSBCI is the bilateral maritime shipping connectivity index which can be obtained from database of UNCTAD STAT.[24] The average GDP per capita in China and a trading country is 37.6 thousand USD per year. We use a distance variable to control for the distance between China and trading partner countries. It is measured as the distance between Beijing and the capital city of each of the trading partner countries. Regional Trade Agreement (RTA) identifies terms that relax trade barriers in service sector and thus can be an important facilitating determinant of service trade. From 2005 to 2018, seven countries signed RTAs with China. Moreover, among 45 countries used in the study, two countries are landlocked. Thus, landlocked variable is a dummy variable that takes values of 0 or 1. The remaining control variables (i.e., common language, contiguous and continent) are also dummy variables that take the value of one if a trading partner uses the same language (i.e., Chinese), shares a common border with China, and is located in Asia, respectively.

To gain further insights into China's service trade volume and air connectivity with specific trading partners, Table 3.1.2 selects 11 China's major service trading partners and

[24] Please refer to the following link:
http://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=96618

presents detailed data on service trade imports and exports, the number of direct routes, and the average passenger number per route between China and these countries. The 11 selected trading partners include the top 10 countries with which China has the largest volume of service trade (total export and import). The Russian Federation is also included because the number of direct routes between China and Russia is high, although the total service trade is low. It is found that both China's service trade and the number of direct routes have increased since 2005, which aligns with observations from Figure 3.1.3. It is interesting to observe that despite the significant variation in the number of direct routes among different partner countries, the average number of passengers per route remains relatively stable (with approximately 50,000 passengers in 2015 for the top three countries). This suggests that China expands air connectivity with major trading partners mainly through adding new destinations, instead of increasing capacity on existing routes. Figure 3.1.5 illustrates the number of direct routes between China and the six partner countries with the highest number of direct routes from 2005 to 2018. The US is the China's largest service trade partner, although the number of direct route ranks the third. From Figure 3.1.5, it is evident that Japan and South Korea have the largest number of direct routes with China, with over 140 direct routes in 2015. The US and Russia come next, with approximately 50 direct routes in 2015. Singapore and Australia have around 30 direct routes.

Based on Table 3.1.2 and Figure 3.1.5, it can be observed that the US, Singapore, South Korea, Japan, and Australia are the top countries with both high service trade volume, and large number of direct routes with China. They all rank among the top ten. Such observations suggest positive correlation between the service trade and the air connectivity in terms of the number of direct routes. However, France and Russia are exceptions. Although France has a large service trade volume with China, ranking fifth, it only had nine direct routes with China in 2015. On the other hand, Russia has a large number of direct routes with China, ranking fourth, but its service trade volume ranks eleventh. These data provide a useful clue of the potential relationship between the service trade and air connectivity. However, to identify the causal relationship between air connectivity and service trade, formal and rigorous empirical analysis is necessary, which will be conducted in the subsequent section.

Table 3.1.1 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Unit
Total export	411	1.706	3.390	Billion USD
Total import	413	3.092	7.236	Billion USD
Direct route	430	9.52	21.00	Route
Average passenger	430	21000	30000	Person
Internet penetration	427	0.503	0.153	Unit
Exchange rate	430	1.26	0.639	Foreign currency per RMB
LSBCI	430	0.381	0.238	Unit
GDP per capita	435	37.567	22.830	Thousand USD
RTA	430	0.084	0.277	Dummy variable
Contiguous	430	0.053	0.225	Dummy variable
Common language	430	0.044	0.206	Dummy variable
Distance	430	7703.34	2447.46	Kilometers
Landlocked	430	0.186	0.39	Dummy variable
Continent	430	0.14	0.347	Dummy variable

Note: The date are shown on a yearly basis.

Table 3.1.2 Descriptive statistics of air connectivity and service trade of selected partners

Partner country		2005	2010	2015
China-US	Service Trade Export (Billion USD)	6.2	10	15
	Service Trade Import (Billion USD)	8.5	22	47
	Direct Route Number	25	30	53
	Average Passenger per Route	27713	43355	51322
China-Singapore	Service Trade Export (Billion USD)	1.4	3.9	15
	Service Trade Import (Billion USD)	1.7	5.6	17
	Direct Route Number	19	23	35
	Average Passenger per Route	59450	60888	59799
China-South Korea	Service Trade Export (Billion USD)	6.4	6.9	9.5
	Service Trade Import (Billion USD)	6	13	20
	Direct Route Number	51	69	145
	Average Passenger per Route	61419	61968	51886
China-Japan	Service Trade Export (Billion USD)	7.6	9	N/A
	Service Trade Import (Billion USD)	6.7	10	N/A
	Direct Route Number	74	88	163
	Average Passenger per Route	43401	48724	35978
China-France	Service Trade Export (Billion USD)	2.2	N/A	6.1
	Service Trade Import (Billion USD)	3.1	N/A	5.5
	Direct Route Number	10	3	9
	Average Passenger per Route	30821	100044	69633
China-Australia	Service Trade Export (Billion USD)	1.1	1.4	1.8
	Service Trade Import (Billion USD)	2.3	5.4	7.4
	Direct Route Number	18	9	21
	Average Passenger per Route	13860	46258	40303

China-New Zealand	Service Trade Export (Billion USD)	N/A	0.18	1.5
	Service Trade Import (Billion USD)	N/A	0.51	7.3
	Direct Route Number	N/A	2	5
	Average Passenger per Route	N/A	26898	39352
China-United Kingdom	Service Trade Export (Billion USD)	1.2	2.1	2.1
	Service Trade Import (Billion USD)	2.4	3.3	4.8
	Direct Route Number	10	2	5
	Average Passenger per Route	22032	126954	87122
China-Denmark	Service Trade Export (Billion USD)	0.69	N/A	1.7
	Service Trade Import (Billion USD)	1.1	N/A	2.3
	Direct Route Number	2	1	3
	Average Passenger per Route	26069	44994	19665
China- Canada	Service Trade Export (Billion USD)	0.74	1.8	1.9
	Service Trade Import (Billion USD)	0.88	1.5	2.1
	Direct Route number	10	4	9
	Average passenger per route	25981	92998	75126
China-Russian Federation	Service Trade Export (Billion USD)	0.97	1.4	1.7
	Service Trade Import (Billion USD)	0.65	1.1	1.5
	Direct Route number	23	30	48
	Average passenger per route	12931	15848	14960

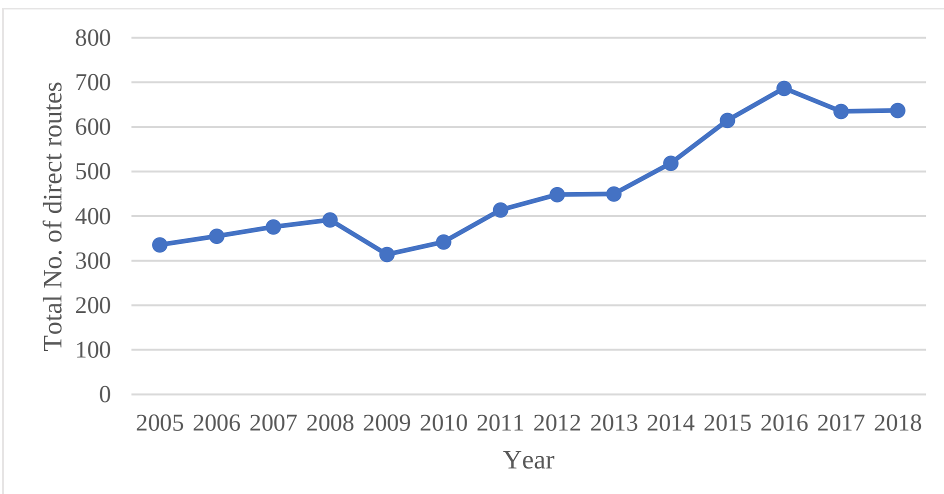

Fig. 3.1.3: The total number of direct routes with sampled trading partners for 2005-2018 period

Source: made by authors with data from IATA PaxIS database.

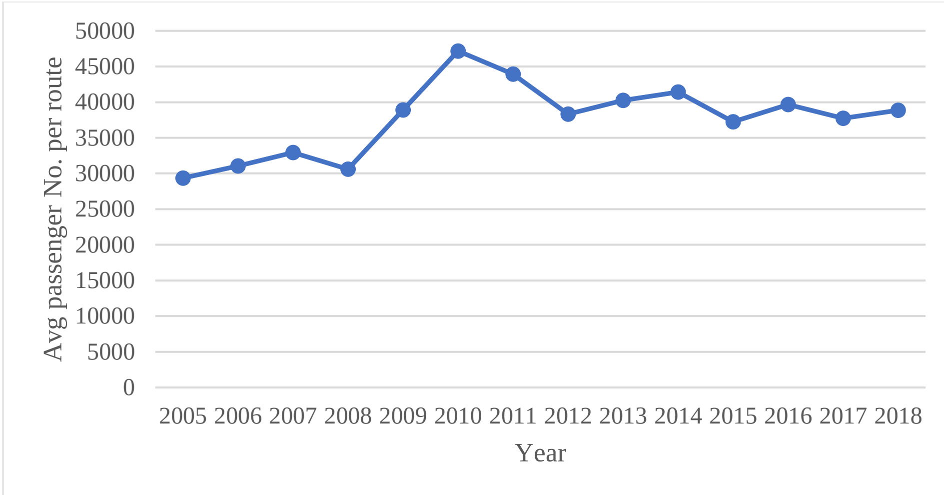

Fig. 3.1.4: The passenger number per direct route with sampled trading partners for 2005-2018 period

Source: made by authors with data from IATA PaxIS database.

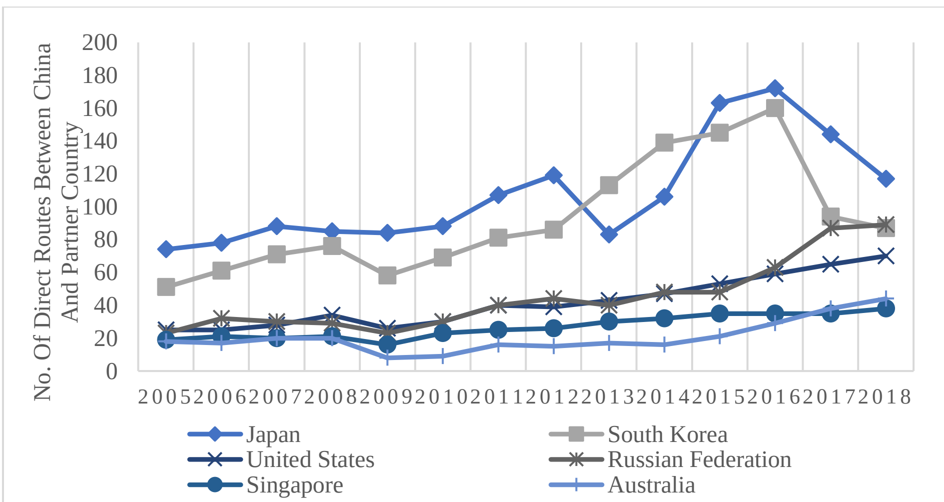

Fig. 3.1.5: The number of direct routes with selected trading partners for 2005-2018 period[25]

Source: made by authors with data from IATA PaxIS database.

3.1.5 Estimation Results and Discussions

This section reports and discusses our estimation results. We use the fixed-effect method to control for the country-pair and time (year) fixed effects. One major drawback of the fixed-effect method is that the effects of the time-invariant control variables cannot

[25] The sudden decrease in the number of direct routes with Japan and South Korea from 2016 can be attributed to the Terminal High Altitude Area Defense (THAAD) issue.

be identified since they are absorbed by the country-pair fixed effects. The random-effect method is also adopted as a robustness check as it enables identification of the time-invariant variables including countries' distance, common language, cultural ties, border contingency and geographic location[26].

Table 3.1.3 shows that our IV significantly affects China's air connectivity measured either by the number of direct routes or by the route-level traffic density. Specifically, when China and a trading partner country increase the number of direct routes to cities in other foreign countries by 1%, the number of direct routes (or the route-level traffic density) between China and this trading partner country increases by 1.042% (or 2.460%). These results show that the relevance restriction for our IV is satisfied.

Table 3.1.3 The first-stage regression results

	No. of direct routes	Route-level traffic density
Connectivity_IV	1.042***	2.460**
	(0.309)	(1.263)
GDP per capita	-0.271*	0.282
	(0.147)	(0.614)
Exchange rate	0.127*	0.378
	(0.0759)	(0.404)
Internet penetration	-0.846*	-3.528*
	(0.475)	(1.937)
RTA	0.471***	-0.185
	(0.128)	(0.214)
LSBCI	0.465	6.497*
	(0.388)	(3.759)

Notes:
1. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
2. The logarithms are taken for the trade variable and other continuous control variables.

3.1.5.1 Service export

In Tables 3.1.4 to 3.1.7, we report the estimated effects of bilateral air connectivity on China's bilateral service export and import, while also distinguishing the air connectivity measurement by the number of direct routes and the route-level traffic density, respectively. It is noted that we did not put these two variables in the same regression for a "horse race"

[26] See Appendix (Tables C2 to C5) for details.

regression. Although such approach can directly show the differential effects of the number of direct routes and the route-level traffic density on the service trade, the significant positive correlation between these two air connectivity variables (as high as 0.53) leads to multicollinearity problem, which makes the coefficient estimators inefficient (i.e., not statistically significant estimated coefficients). Tables 3.1.4 and 3.1.5 demonstrate the impact of bilateral air connectivity on service export. An improvement in air connectivity shows a positive effect on China's total service export. In addition, the number of direct routes has a stronger positive impact than route-level traffic density. Moreover, China's commercial service export is mostly stimulated by an increase in the number of direct routes with its trading partners. The elasticity between the commercial service export and the number of direct routes is approximately 1.54. The commercial services require face-to-face meetings to build business relationships and explore new business opportunities. Thus, to improve commercial service export, China needs to open direct flights to more destinations to make it more convenient for Chinese business travelers to reach their destinations (i.e., the potential business markets).

However, the subcategories of service exports are not very responsive to the change in the average passenger number per route including transport, travel and commercial service. This also suggests that service export opportunities are not enhanced by more frequent travel on existing direct origin-destination (OD) pairs. Thus, a marginal gain from an increase in the route-level traffic density is limited.

A transport export service variable refers to the revenue earned by the Chinese carriers. This variable is significantly and positively affected by the number of direct routes, whereas it is not affected by a route-level traffic density. While increasing the number of direct flight services to more foreign destinations may be beneficial for Chinese carriers, expanding the route-level traffic density may not help generate higher revenue. Moreover, for the travel service export we find no positive effect from the bilateral air connectivity. This result may imply that travelers from foreign countries and students are not affected by improvements in the air connectivity between China and their trading countries in terms of the number of direct routes or route-level traffic density. Similarly, the government service import, is not significantly affected by the bilateral air connectivity.

In addition, we find that GDP per capita is a major contributor to the China's bilateral service export. The internet penetration also facilitates service export, and its effect could be more prominent than the air connectivity, except for the commercial service export. This suggests that several commercial service trades are conducted through the internet including digital product service (i.e., software and other copyright license etc.). As shown in Table 3.1.1, the mean value of the internet penetration variable is 0.503, suggesting that on average half of populations in China and trading partner companies have access to the internet. The standard deviation of this variable is also relatively small, implying that internet access is extremely high among sampled countries. Therefore, the marginal impact of the internet penetration on commercial service export could be limited. Our estimations also demonstrate the importance of face-to-face meetings when seeking for commercial service business opportunities. LSBCI variable measures the maritime shipping connectivity between China and the trading partners. We find that higher LSBCI can improve the merchandise trade by more than 80% in goods trade through international shipping. However, service trade is not significantly affected by the maritime shipping connectivity. Therefore, this finding indicates that the service trade is mainly achieved through human interactions (i.e., face-to-face meetings). In addition, it suggests that there is only weak positive relationship between merchandise and service trades or the little overlap between these two trade networks, at least for the case of China.

Our study focuses on the period before the COVID-19 pandemic. Now, many face-to-face meetings have been replaced by virtual meetings. On the one hand, the increased number of virtual meetings may strengthen the impact of the internet penetration on commercial service trade. On the other hand, the existing restriction on international air travels may weaken the effect of the internet access on transport and travel service trades. However, the effects of the COVID-19 pandemic need to be further investigated in a more sophisticated research framework and with more recent service trade data available.

Table 3.1.4 The impact of No. of direct routes on service export

	Total export	Transport export	Travel export	Commercial export
No. of direct routes	0.666***	0.535**	-0.368	1.540***
	(0.213)	(0.229)	(0.262)	(0.516)

GDP per capita	0.822***	1.324***	0.825***	0.524
	(0.233)	(0.293)	(0.315)	(0.498)
Exchange rate	-0.393	-0.0997	-1.114***	-0.0409
	(0.350)	(0.348)	(0.203)	(0.404)
Internet penetration	-0.183	-1.029	3.269***	-1.591
	(0.840)	(0.915)	(1.070)	(1.737)
RTA	0.209	-0.198	0.344*	-0.0247
	(0.203)	(0.224)	(0.200)	(0.419)
LSBCI	0.901	1.231	-1.394	-0.592
	(0.682)	(0.811)	(0.959)	(1.502)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.1.5 The impact of route-level traffic density on service export

	Total export	Transport export	Travel export	Commercial export
No. of passengers per route	0.403*	0.370	-0.244	0.751
	(0.219)	(0.237)	(0.217)	(0.584)
GDP per capita	0.837***	1.375***	0.863**	1.207
	(0.294)	(0.345)	(0.366)	(0.771)
Exchange rate	-0.473	-0.158	-1.097***	-0.751
	(0.295)	(0.292)	(0.238)	(0.467)
Internet penetration	1.999***	0.815	2.041***	1.580
	(0.705)	(0.780)	(0.687)	(1.393)
RTA	0.340*	-0.106	0.235	0.670*
	(0.195)	(0.213)	(0.189)	(0.385)
LSBCI	-1.988	-1.630	0.722	-4.127
	(2.340)	(2.553)	(2.429)	(6.954)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.1.5.2 Service import

Tables 3.1.5 and 3.1.6 show that air connectivity facilitates China's bilateral service import. An increase in the number of direct routes has a larger and a more statistically significant positive impact on the service import. While the elasticity between bilateral total service import and the number of direct routes is about 1.52, it is only 0.64 between the route-level traffic density. We also find that the transport, travel, and commercial services are more responsive to the number of direct routes. Higher route-level traffic density stimulates transport and travel service import, while has no effect on commercial service import. Thus, to improve commercial service import, a country needs to open direct flights to more destinations to make it more convenient for business travelers to reach their destinations (i.e., the potential business markets). In other words, commercial service import has a higher potential in the secondary Chinese cities, because the mega-city markets such as Beijing, Shanghai and Guangzhou has already been saturated.

The travel service import includes Chinese passengers' education, tourism and health care services spent overseas. The estimation results show that an increase in the number of direct routes brings a larger degree of travel import (more Chinese travelers) than increasing the route-level traffic density. This suggests that the Chinese growth of overseas travel spending is mainly driven by the passengers from the secondary cities with the newly added direct international flights. This is consistent with the observations of higher growth speed and huge potential of overseas travels in the China's secondary cities (e.g., Liu and Oum, 2018).

Among different subcategories, China's transport service import is the most responsive to air connectivity improvement. Transport service import includes Chinese passengers' airfares paid to the foreign airlines. Thus, an increase in the number of direct routes helps foreign carriers to receive more revenue when flying to China. This finding is consistent with the observed expansion of the foreign airlines in Chinese market. Liu and Oum (2018) find that the foreign airlines, especially the low-cost carriers (LCC) from Southeast Asia are more aggressive in expanding the number of direct routes to China's secondary cities where the demand for overseas travel has been growing more rapidly than at China's mega cities. This is also facilitated by China's liberalized aviation policy with Southeast Asian countries (i.e., ASEAN). Carriers in Japan and Korea are eager to expand the number of direct routes to China.

Other control variables such as 'internet penetration rate' is found to significantly promote service trade. This result is intuitive in that some service trades can be conducted in a digital format or through virtual online meetings (i.e., commercial service trades). Thus, the internet availability can substitute air travel and may have a large positive impact on service trade. Our estimation results also shows that internet penetration rate has a higher positive elasticity of China's bilateral service import than even the air connectivity improvement. Also, internet penetration has a positive effect on transport and travel service import since the internet platform facilitates air ticket sales and helps promote travel opportunities.

In addition, the GDP per capita has a marginal effect on China's total service import, while the exchange rate and RTA are not effective in promoting service import. This finding does not align with the effect of the exchange rate and RTA on merchandise trade as suggested by previous trade studies. This result could be due to the service trade being mostly consumed by a high-income population and service-related companies who are more price inelastic and thus less affected by the changing prices caused by the exchange rate fluctuation or tariffs.

Table 3.1.6 The impact of No. of direct routes on service import

	Total import	Transport import	Travel import	Commercial import
No. of direct routes	1.523**	2.409***	1.693**	1.074**
	(0.593)	(0.808)	(0.664)	(0.495)
GDP per capita	0.779**	0.745	0.271	0.211
	(0.343)	(0.493)	(0.474)	(0.730)
Exchange rate	-0.379	-0.831**	-1.002***	-0.416
	(0.320)	(0.389)	(0.383)	(0.455)
Internet penetration	3.062***	3.288***	4.388***	5.147***
	(0.698)	(1.009)	(0.839)	(1.093)
RTA	-0.417	-1.114**	-0.509	0.0157
	(0.348)	(0.490)	(0.554)	(0.503)
LSBCI	-0.659	-1.784	-0.495	-2.505
	(1.138)	(1.488)	(1.613)	(1.650)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.1.7 The impact of route-level traffic density on service import

	Total import	Transport import	Travel import	Commercial import
No. of passengers	0.645**	0.976*	0.661**	0.716
per route	(0.331)	(0.541)	(0.326)	(0.503)
GDP per capita	0.184	-0.198	0.241	1.039
	(0.439)	(0.787)	(0.498)	(0.818)
Exchange rate	-0.430	-0.660	-0.892**	-0.622
	(0.363)	(0.465)	(0.350)	(0.480)
Internet penetration	4.050***	4.678***	4.211***	1.564
	(1.013)	(1.702)	(1.098)	(2.502)
RTA	0.420**	0.250	0.496	0.802
	(0.208)	(0.244)	(0.331)	(0.573)
LSBCI	-4.143	-7.620	-2.647	3.500
	(3.474)	(6.020)	(3.440)	(3.430)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.1.5.3 *Service import vs. export*

The above two subsections examine the effects of air connectivity on service export and import, respectively. In this subsection, we do direct comparison to infer the impact of air connectivity on trade surplus and deficit. In Table 3.1.8, we combine the estimated elasticities of service export and import for total, commercial, travel and transport, to obtain the elasticities of service trade surplus or deficit.

We find that an improvement in air connectivity would increase China's existing overall service trade deficit, especially when China increases the number of direct flight routes with its trading partners. The trade deficit is mainly driven by China's transport and travel services. Thus, foreign carriers would profit more from it than Chinese carriers through the increased number of Chinese people travelling abroad for tourism, education, and health care purposes. However, Chinese commercial trade surplus can be enhanced by increasing the number of direct routes with trading partners. That is, Chinese firms and business organizations can obtain more commercial service exporting opportunities than their foreign counterparts since this will enable them to reach more destinations. This is consistent with the evidence that China has invested heavily in BRI countries with a high share the funding allocated to construction projects. As a result, more efficient air travels between China and the trading countries would facilitate the investments and contract signing opportunities. However, as suggested by Wang et al. (2020a), China's air connectivity with BRI countries is relatively underdeveloped. Thus, there exist a great opportunity for China to stimulate commercial service export trade around the world, in particular with BRI countries.

This study estimates the impacts of air connectivity on China's different service trade categories. Multiple regression equations are estimated with different dependent variables, while they could be correlated as different trade categories could be affected by common unobservable factors. Therefore, a Seemingly Unrelated Regression (SUR) model could be useful to improve our estimation efficiency by jointly estimating these regression equations, which fully utilize the correlations among different regression equations. The SUR does not solve the endogeneity issue, so that we need to combine it with 2SLS using our IV for the first stage regression. The first stage regression remains the same as presented in Table 3.1.2. In the second stage, the SUR model is employed to improve the estimation efficiency by estimating multiple regressions simultaneously. Specifically, we jointly estimate the regressions with different dependent variables of the service trade (total service export/import, commercial service export/import, travel service export/import, transport export/import). The summary results of the second stage are presented in Table 3.1.9 to show the calculated elasticity of service trade to air connectivity using SUR estimations, while more detailed SUR regression results can be found in Tables C6 and C7 in the Appendix.

Overall, SUR produces more significant estimated effects of air connectivity on service trade. That is, the signs of the estimated coefficients are consistent with our original estimations, but are more statistically significant. In particular, with SUR, the number of passengers per direct route is now found to have significantly positive impacts on China's commercial service import and export. The major findings are still qualitatively unchanged with SUR. It is still true that the number of direct routes is more effective than the number of passengers per route to promote China's service trade. The commercial service exports can be stimulated more than the imports.

Table 3.1.8 The summary of estimated elasticity between service trade and air connectivity

Service trade elasticity	No. of direct routes	No. of passengers per route
Total Import	1.532**	0.645**
Total Export	0.666***	0.403*
Total Surplus	-0.866***	-0.242*
Transport Import	2.408***	0.976*
Transport Export	0.535**	0.37
Transport Surplus	-1.873***	-0.606
Travel Import	1.693**	0.661*
Travel Export	-0.368	-0.244
Travel Surplus	-2.061**	-0.905
Commercial Import	1.074**	0.716
Commercial Export	1.540***	0.751
Commercial Surplus	0.466***	0.035

Notes:
1. *** p<0.01, ** p<0.05, * p<0.1
2. For those results without statistical significance, we are unable to make a valid inference.
3. The negative sign for trade surplus means the trade deficit.

Table 3.1.9 The summary of estimated elasticity between service trade and air connectivity (SUR)

Service trade elasticity	No. of direct routes	No. of passengers per route
Total Import	1.401**	0.594**
Total Export	1.145**	0.485**
Total Surplus	-0.256	-0.108
Transport Import	1.725**	0.731**
Transport Export	0.609	0.258
Transport Surplus	-1.117	-0.473
Travel Import	1.781**	0.755**
Travel Export	-0.408	-0.173
Travel Surplus	-2.190***	-0.928***
Commercial Import	2.335**	0.989**
Commercial Export	2.451***	1.039***
Commercial Surplus	0.117	0.049

Notes: *** p<0.01, ** p<0.05, * p<0.1
1. For those results without statistical significance, we are unable to make a valid inference.
2. The negative sign for the trade surplus means the trade deficit.

3.1.6 Summary

In this study, we examine how air connectivity affect bilateral service trade flow. We chose to use the number of direct flight routes between the country-pair and the average passenger number per route (passenger density) as our measure of air connectivity for this research. Our service trade data includes 'commercial' services, 'transport' services,' travel' services. Using Chinese data, a reduced-form gravity-type model is estimated. We used IV approach in order to deal with the potential endogeneity between bilateral air connectivity and bilateral service trades.

Our findings suggest that an increased number of direct routes can significantly promote bilateral service trade export and import, while the average passenger number per route has a marginal effect. Furthermore, an improvement in bilateral air connectivity stimulates China's total service import more than export (especially for transport and travel services), thus expands the overall service trade deficit for China. Also, an increase in the air connectivity can facilitate 'commercial' service export, while contributing to the surplus in China's commercial service trade sector, which accounts for more than 50% of the China's total service trades. To promote its bilateral service trade, China should expand the number of direct routes with its trading partner countries, instead of increasing flight frequencies on the existing routes. In other words, the priority should be given to relax restrictions on the destinations with direct flights, instead of lifting the restrictions on the route-level flight frequencies.

Our results are derived from the real world data and are also linked with the previous research. However, this study has important limitations. First, our data is only available for the period before COVID-19 pandemic. The current international connectivity has been significantly restricted due to the pandemic, especially for China, which is implementing the “zero-case” policy. As a result, the effect of air connectivity on service trade may be altered by changing travel behaviors and the substituting face-to-face meeting with virtual online meetings. Thus, future studies should be conducted to investigate the COVID-19 impact when the data becomes available. In addition, our gravity-type model is a reduced-form approach, which measures only the net causal effect of air connectivity on bilateral service trade flow. That is, the detailed mechanisms via which service trades are stimulated are not directly addressed in this study since such study would require the use of a more sophisticated approach by both academics and policymakers. Lastly, on purpose we chose to use rather simple air connectivity measures because the enormous data needs for constructing air connectivity between China and each of 45 service trade partner countries for each year of 2005-2018. Unlike other studies focusing on connectivity measurement for specific node (i.e., airport or city) in a network, it would be difficult for us to use a more sophisticated connectivity index for each country-pair and each year of our time series. Thus, we chose to use the number of direct routes and average passenger density per route as our air connectivity measures. Another limitation of this study is the restricted coverage of our dataset, which includes only 45 Chinese service trading partners. Such data limitation is because the service trade data is voluntarily reported by the countries' governments, such that the records with some trading partners could be hidden for data quality or national security reasons. Although our data only covers a subset of Chinese service trading partners, the selected 45 sample trading partners actually represent a mix of major partner countries such as the US, Japan, South Korea, and Singapore, as well as smaller partner countries like Slovenia, Croatia, Malta, and Belarus. The level of air connectivity between China and the 45 countries also varies significantly, with some highly connected countries like Japan and the US, and some countries without direct flight connections like Ireland and Serbia. Such significant heterogeneity among our sample countries could somewhat justify the validity of our empirical estimations. If more complete data becomes available later on, future research could consider expanding the dataset to encompass all the countries with service trade with China to provide more generalized research findings. All of these limitations stated here suggest meaningful directions for extending the current research in the future.

3.2 The case of the United States: Focus on the Impact of Open Skies Agreements and OSA Lead and Lag Effects

3.2.1 Abstract

This study measures the effects of the US Open Skies Air Services Agreement (OSA) on bilateral service export and import trades with each of the 191 trade partners over the 2005-2019 period. Our US service trade data includes ‘commercial’, ‘transportation’, and ‘travel’ service sectors. Service trade includes many of the sectors essential for building post-industrial economy of a nation. An instrument variable (IV) approach is adopted to address the endogeneity between OSA and the service trade variables. Using reduced-form gravity type difference-in-differences (DID) regression, we find OSA has a significant positive effect on transport and travel exports and imports. However, the OSA impact on US commercial service exports is insignificant while being significantly positive on US service imports. We also found a significant positive one-year lead effect as well as three-years lag effects of OSA on bilateral service trades.

3.2.2 Introduction

Post-industrial economies tend to place greater emphasis on services than traditional manufacturing industries. As automation and technological advancements continue to reshape the global economy, services such as finance, information technology, healthcare, and education become increasingly vital. Service trade enables countries to leverage their expertise in these sectors, fostering economic growth, employment and competitiveness (El Khoury & Savvides, 2006; Arnold et al., 2011). According to World Bank statistics, the global service trade value has grown significantly, from US$5.39 trillion in 2005 to

US$13.78 trillion in 2022[27]. In 2022, the trade in services to GDP ratio was 13.4% globally[28]. For some countries, such as Luxembourg, Malta, Singapore, and Ireland, this ratio exceeded 100% in 2022. The proportion of people employed in the service sector has also increased, growing from 43% in 2005 to 50% in 2022. Countries or regions like Luxembourg, Hong Kong, Singapore, Macao, Netherlands, Malta, and the United Kingdom have more than 80% of their workforce in the service sector in 2022.

As a highly developed economy with a diverse range of service industries, the US benefits immensely from the export of services. According to World Bank data, the US's service export value is the highest, reaching US$928.5 billion in 2022, with the UK ranking second with US$505.3 billion. Barattieri (2014) calculated the Revealed Comparative Advantage index in services, revealing that the US possesses a significantly higher advantage in service exports compared to Japan, Germany, and China. Industries such as finance, technology, entertainment, healthcare, and consulting contribute significantly to the country's service exports. Figure 3.2.1 illustrates the dramatic increase in total service trade in the US, which increased from US$705 billion in 2005 to US$1,628 billion in 2019. Figure 3.2.2 provides a breakdown of service exports and imports in the commercial, travel, and transport sectors of the US between 2005 and 2019, with commercial services accounting for over 50% of the total service trade. Figures 3.2.3 and 3.2.4 show the distribution of US service exports and imports worldwide in 2019. Service trade enables the US businesses to expand their reach beyond domestic borders, tap into international markets, and capitalize on their expertise, intellectual property, and skills. By exporting services, the US generates revenue, attracts foreign investment, and strengthens its trade balance. Moreover, the provision of services often involves close collaboration with foreign partners, leading to knowledge exchange, cross-cultural understanding, and the development of global networks. The continual growth and international competitiveness of the US service sector are crucial for sustaining economic dynamism, fostering innovation, and maintaining the country's position as a global economic leader.

The transportation system plays a pivotal role in facilitating both merchandise trade

[27] The data is from https://stats.wto.org/.

[28] Trade in services (% of GDP) is the sum of service exports and imports divided by the value of GDP and the data is from https://data.worldbank.org/indicator/BG.GSR.NFSV.GD.ZS?most_recent_value_desc=true.

and service trade, serving as a vital link between producers, consumers, and markets (Besedeš et al., 2024; Boddin & Stähler, 2024; Coşar & Demir, 2016; Friedt & Wilson, 2020; Hummels, 2007; Romalis, 2004; Volpe Martincus & Blyde, 2013). For merchandise trade, an efficient transportation infrastructure enables the movement of goods across domestic and international borders, connecting manufacturers with suppliers and customers worldwide. It ensures the timely delivery of raw materials, components, and finished products, thereby supporting supply chains and enabling global trade networks to function smoothly (Bensassi et al., 2015; Clark et al., 2004; Wong, 2022). Similarly, for service trade, transportation systems are essential in facilitating the movement of people, knowledge, and expertise. Several studies have emphasized the significance of movement of people for trade (Herander & Saavedra, 2005; Jansen & Piermartini, 2009). Service providers often need to travel to deliver their services, participate in conferences, or engage in face-to-face interactions with clients. A well-connected transportation network, especially the air network, ensures the seamless mobility of service professionals, enabling them to reach their destinations efficiently and promptly. Moreover, air connectivity contributes to the growth of service sectors such as tourism, hospitality, and logistics, as they provide the necessary means for visitors and tourists to access various destinations and for goods and services to be distributed effectively.

Since 1992, the US has pursued a policy of actively seeking “Open Skies” air transport agreements. An Open Skies Agreement (OSA) typically refers to a treaty between two or more countries concerning civil aviation services, aimed at eliminating government intervention in international air transport services. This includes the relaxation of restrictions on airline routes to be served, airfare, flight frequency and the designated airlines. Such agreements generally promote the liberalization of the aviation market, increase flight frequency and market competition, and reduce airfare costs, thereby stimulating tourism, transportation, and commercial activities (Micco & Serebrisky, 2006; Oum et al., 2019). The goal is to enable airlines to offer more affordable, convenient, and efficient air services to consumers. By promoting increased travel and trade, these agreements also contribute to the creation of high-quality jobs and stimulate economic growth. According to a study conducted by Winston and Yan (2015), the OSAs signed between the US and other countries have generated an annual gain of 4 billion USD for US international travelers. The US has signed OSAs with more than 135 countries or regions by 2023. These OSA partnerships span a wide range of economies, including major economies such as Brazil, India, and South Korea, as well as smaller nations like Brunei, Cabo Verde, and Rwanda. Currently, more than 70 percent of international departures from the US are directed towards Open Skies partner destinations[29].

Although there are plenty of studies investigating the impact of transport connectivity on the merchandise trade (Bensassi et al., 2015), few studies explore the impact of transport connectivity on the service trade, especially with the dramatically increasing service trade around the world and air liberalizations with more OSA signings. To the best of our knowledge, Oum, Wang, and Yan (2019) is the first study to explore the impact of Canada's OSA and the US OSA on Canada's service exports. Oum et al. (2024) also investigate the impact of air connectivity on bilaterial service trade in the context of China. However, since China and Canada are not active in liberalizing its international air services, both studies do not connect the OSA and the resultant air connectivity expansion together with the service trade. On the other hand, as mentioned earlier, the US has been a trailblazer in signing OSAs and promoting the liberalization of international air services. Furthermore, the US is a global leader in both service trade exports and imports. An important potential benefit of the US's extensive efforts to liberalize its international air services is the significant stimulation of its service trade with the rest of the world. Establishing a causal relationship between these factors is crucial in justifying the economic gains associated with signing OSAs. Therefore, conducting dedicated and comprehensive empirical investigations in the US is particularly meaningful, as it represents a highly relevant subject. The findings from this study could provide valuable implications for countries like China and India, which have relatively conservative international air policies but are experiencing growth in their service trades.

In addition, the OSA negotiation process among countries often spans several years. During this period, airlines and airports may anticipate positive impacts on the market even before the OSA is officially signed and implemented. Such anticipation can result in the early manifestation of OSA effects. On the other hand, there may also be a lag effect, as service trade imports and exports involve complex supply chains and information

[29] The data is from https://www.state.gov/.

dissemination. Business stakeholders may require time to adapt and respond to the signing of OSAs between two countries. However, studies on the lead and lag effects of OSAs, as well as the specific timing of such effects, are relatively limited.

Taken together, this study aims to contribute to the current literature by figuring out the causality between OSA and service trade, as well as the lead and lag effect of OSA. Furthermore, this study will investigate the impact of OSA on air connectivity to verify the mechanism of OSA's effects on the service trade. To deal with the endogeneity issue, we propose an instrument variable (IV) for the estimations.

The remaining sections of this study are structured as follows: Section 3.2.3 provides a comprehensive review of the relevant literature. In Section 3.2.4, we present the data sources and outline the specifications of the econometric model. Additionally, we provide a detailed explanation of the IV approach employed to deal with the endogeneity concern for our empirical estimation. The empirical findings are presented and analyzed in Section 3.2.5. Section 3.2.6 conducted a mechanism analysis. Finally, Section 3.2.7 concludes the study.

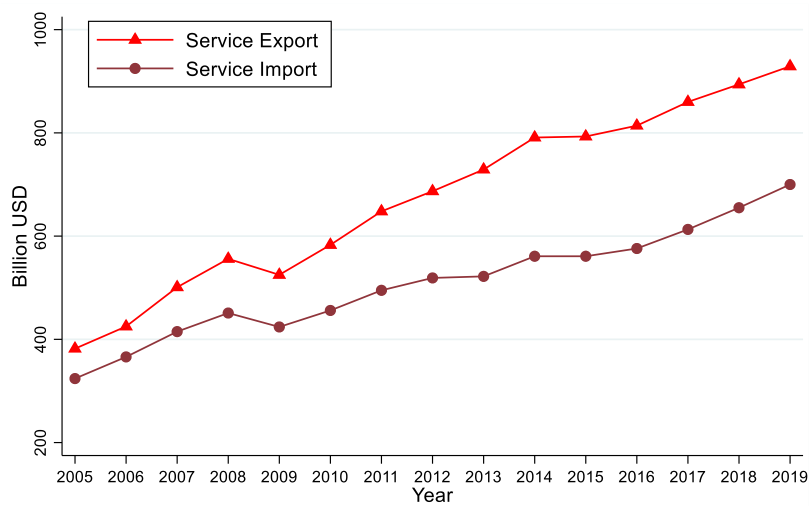

Fig. 3.2.1: US service exports and imports
Note: This figure plots the increasing trend of US service exports and imports over time. (billion US$)
Source: Compiled by authors based on the data from the WTO Stats portal (https://stats.wto.org/).

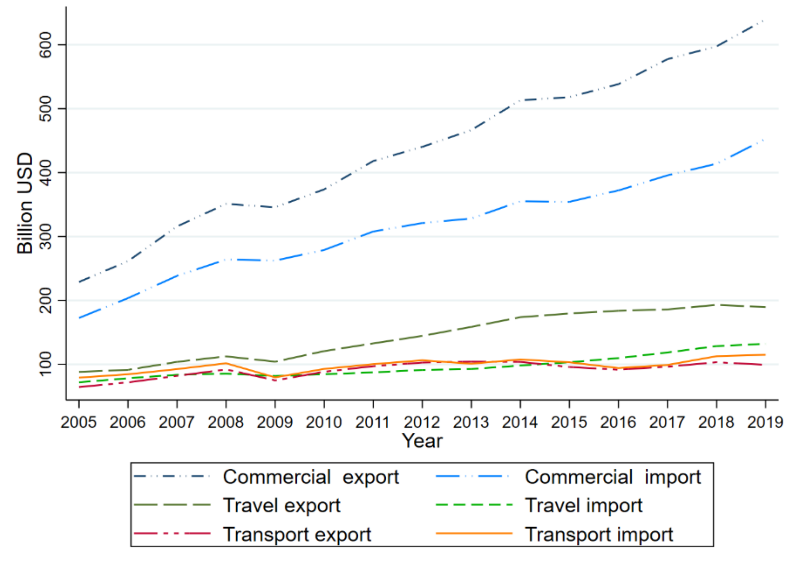

Fig. 3.2.2: US service exports and imports by subsector
Note: This figure plots the evolution of US commercial, travel and transport imports and exports over time (2005-2019).
Source: Compiled by authors based on the data from the WTO Stats portal (https://stats.wto.org/)

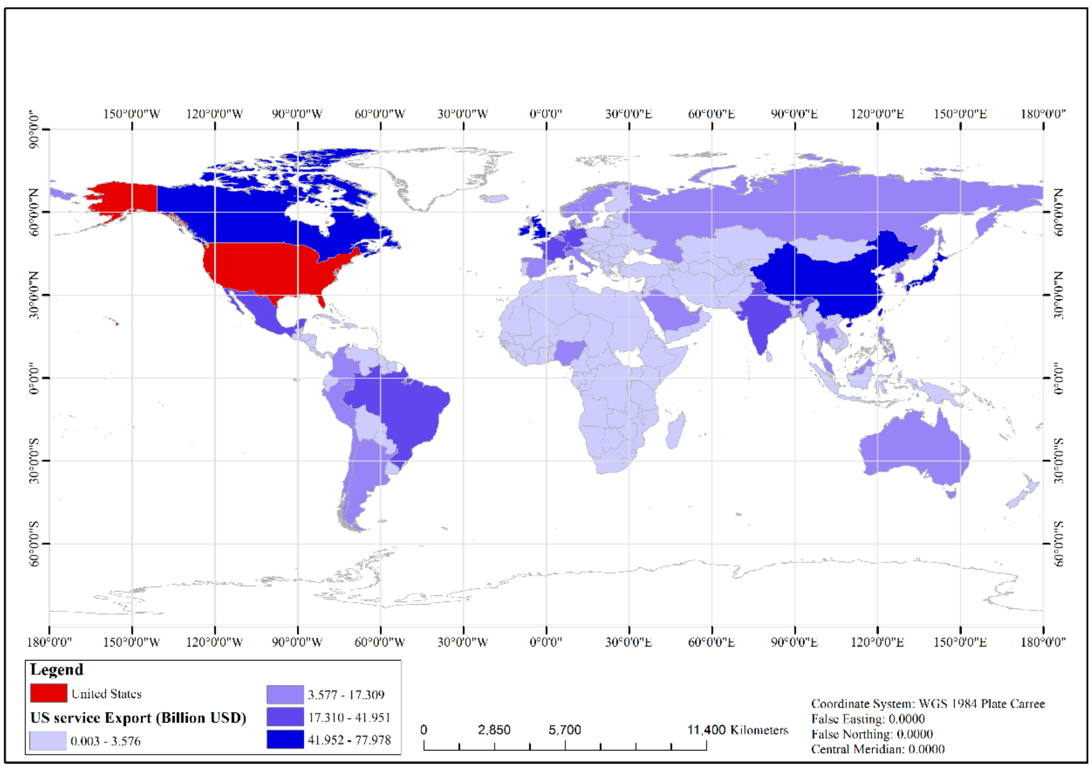

Fig. 3.2.3: Country distribution of US service trade exports in 2019
Notes: This figure shows the country or region distribution of US service trade exports, where darker colors indicate higher levels of service trade exports from the US to that partner. The map is for illustrative purposes only and does not imply the authors' opinion of the legal status of any country, territory, city or region, or its authorities, nor does it represent any opinion on the delimitation of boundaries or frontiers (applicable to all maps in this thesis).
Source: Compiled by authors based on the data from the WTO Stats database and Esri (www.esri.com).

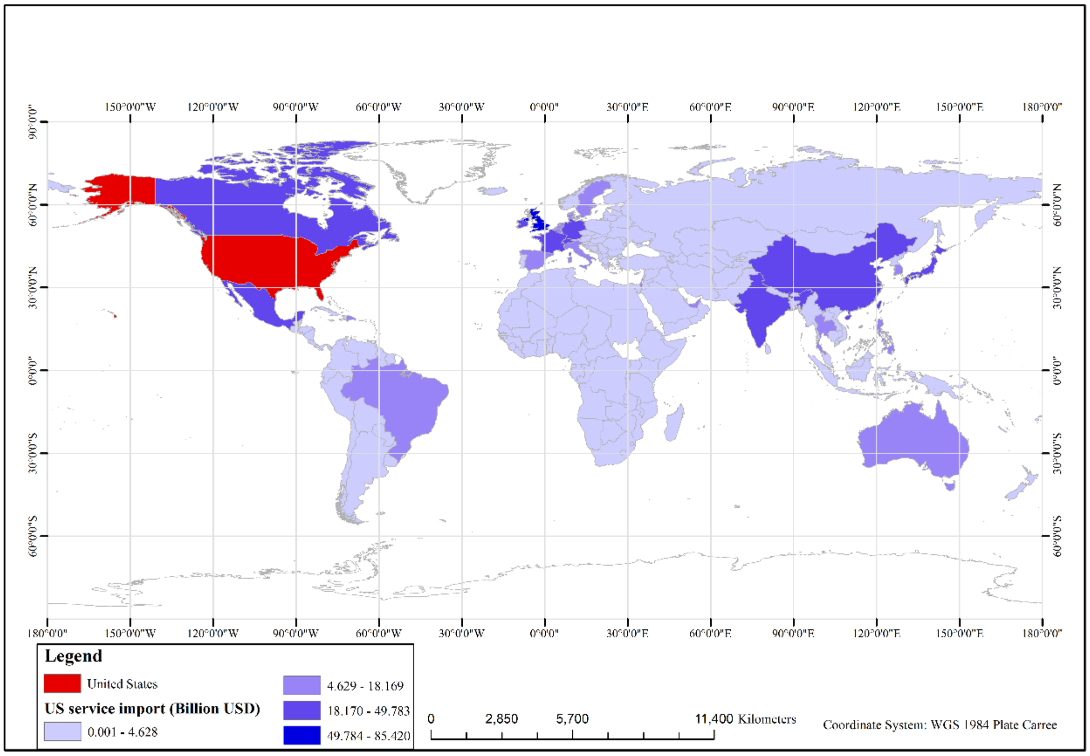

Fig. 3.2.4: Country distribution of US service trade imports in 2019
Note: This figure shows the country or region distribution of US service trade imports, where darker colors indicate higher levels of service trade imports of the US from that partner.
Source: Compiled by authors based on the data from the WTO Stats database and Esri (www.esri.com).

3.2.3 Literature Review

This study is related to two streams of literature: the benefit of OSAs on economic growth and the impact of air liberalization on bilateral trade.

3.2.3.1 OSAs and economic growth

Many countries, particularly the US, are enthusiastically signing OSAs to facilitate air liberalization and transportation connectivity. This section provides an overview of the multifaceted benefits associated with air transport liberalizations, particularly OSAs. The literature indicates that OSAs can generate improvements in consumer welfare, carrier performance, and airline profitability; enhanced transportation connectivity, service quality, and flight frequencies; boosts to tourism and related economic activity; as well as broader macroeconomic gains, including increased local output, investment, employment, international trade, and overall economic development (Micco & Serebrisky, 2006; Oum et al., 2019; Brueckner, 2003a; Cristea et al., 2015).

The extant literature offers several pertinent insights on the impacts of air service liberalization policies. For instance, Winston and Yan (2015) estimate that US OSAs have generated $4 billion in annualized passenger welfare gains, while highlighting the potential for an additional $4 billion in benefits if such policies were extended to major aviation markets. Additionally, in a comprehensive analysis of 2,300 Air Services Agreements (ASAs). Similarly, Piermartini and Rousová (2013) find that the implementation of OSAs and European Economic Area-type liberalization can increase global passenger traffic by 5% and 10% respectively. From the other side, the liberalization of air services promotes market competition, which assumed in turn reduces price dispersion (Gerardi & Shapiro, 2009). With reduced price dispersion, consumers can more easily compare prices when choosing flights, leading to more informed decisions. Collectively, the extant literature suggests that OSAs can yield substantial benefits in terms of enhanced consumer welfare, improved carrier performance, and broader economic impacts stemming from increased transportation connectivity. Crucially, the consensus finding is that the establishment of OSAs serves as a key mechanism to facilitate air service liberalization and connectivity.

3.2.3.2 Air liberalization and bilateral trade

This study also seeks to expand the literature on the effects of air transport liberalization, specifically OSAs, on bilateral service trade. Existing research has examined diverse factors influencing bilateral service and cargo trade, including economic size, geographic distance, trade agreements, and logistics (Cox & Harris, 1985; Cai & Treisman, 2005; Anderson et al.,2014). A substantial body of research has established the close relationship between bilateral trade and international transport development (Geraci & Prewo, 1977; McCallum, 1995; Hummels, 2007; Wong, 2022). Specifically, some studies have found that the agreements about air transport, such as OSAs and ASAs, can influence international trade through various dimensions, including air connectivity, trade costs, and air passenger traffic. Emlinger and Guillin (2024) examine the impact of ASAs on trade from the perspectives of time and cost. The results indicate that ASAs reduce transportation costs by 8%, while their effect on transportation time is significant primarily for landlocked countries and members of regional trade agreements (RTAs). Lee and Cho (2017) find that encouraged air transport services from the provisions in FTAs may promote service trades using OECD data from 2003 to 2006.

The literature on the relationship between OSA and goods trade is extensive. Numerous studies have found that OSAs play a crucial role in promoting goods trade. Piermartini and Rousová (2013) argued that signing ASAs can promote bilateral trade in goods through increased passenger traffic. Similarly, Micco and Serebrisky (2006) found that OSAs can influence international trade by reducing transportation costs. Particularly for developed and upper-middle-income developing countries, OSAs reduce air transport costs, leading to an increase in trade of about 12%. However, research on the relationship between service trade and OSAs remains limited. In fact, several studies have found that air transport can have important effects on service trade. For instance, Cristea et al. (2015) use detailed data on worldwide passenger aviation in the Middle East market to finds that more liberal air transport policy is associated with greater passenger traffic between countries. Liu and Oum (2018) argue that under the China-ASEAN OSAs, more efficient and convenient air services in China would help the tourism and international trade sectors that airlines need to support. Particularly, OSAs are found to be the most effective in promoting 'commercial' service export and import trades (Oum et al., 2019).

Building on the research method of Oum et al. (2024), the present study aims to investigate the relationship between OSAs and bilateral export and import of services. Overall, research on the linkages between OSAs and service trade remains limited, and the specific impact paths and characteristics of OSAs on service trade have not been comprehensively discussed, particularly in the context of the US and other countries. This study can contribute to the expansion of research on the development of air transport and bilateral service trade, especially in the context of bilateral agreements.

3.2.4 Econometric Model and Data Description

Similar to Oum et al. (2024), we adopt a reduced-form gravity-type equation to examine the impact of OSA on bilateral service trade.[30] The general structure of our gravity model is specified as follows in equation (3.2.1),

---

[30] In spirit of the gravity model used in merchandize trade, Walsh (2008) is the first study to adopt the gravity model to examine the determinants of bilateral service trade, and find the model works well.

$$\begin{aligned}\ln Y_{it} = \alpha_1 + \beta_1 \times OSA_{it} + \gamma_1 \times RTA_{it} + \gamma_2 \times Internet\ Penetration_{it} \\ + \gamma_3 \times LSBCI_{it} + \gamma_4 \times \ln ExchangeRate_{it} \\ + \gamma_5 \times \ln\ GDP\ per\ capita_{it} + \mu_i + \rho_t + \varepsilon_{it}\end{aligned} \tag{3.2.1}$$

where subscript i denotes a service trading partner country and the subscript t denotes the year. Y_{it} is the dependent variables, including, $Commercial\ service\ export$, $Transport\ service\ export$, $Travel\ service\ export$, $Commercial\ service\ import$, $Transport\ service\ import$, $Travel\ service\ import$. According to the 2010 Extended Balance of Payments Services Classification (EBOPS 2010), we categorize the service trade into three subsectors: "commercial service", "transportation service", and "travel service", as presented in Table 3.2.1. We exclude "government service trade" from our analysis as it is more closely associated with political issues, and it is less than 1% of total service trade. Thus, the total service trade in this study is the combined sum of these three subsectors. The variables in the equation (3.2.1) are defined as follows:

- Y_{it}: service trade value from US to partner i in year t. The data is obtained from WTO Stats portal (https://stats.wto.org/).
- OSA_{it}: A dummy variable indicating whether the US has signed an OSA with partner country or region i in year t. If the OSA was applied before October of year T, $OSA_{it} = 1$ since $t \geq T$. If the OSA was applied in October, November, and December of year T, $OSA_{it} = 1$ since $t \geq T + 1$. The data is obtained from the US government website (https://www.state.gov/civil-air-transport-agreements).
- RTA_{it}: A dummy variable indicating whether there are regional trade agreements between the US and partner i in year t. The data is obtained from the WTO Regional Trade Agreements Database.
- $Internet\ Penetration_{it}$: the percentage of the population in partner i using the internet in year t. The data is obtained from the International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database.
- $LSBCI_{it}$: the Liner Shipping Bilateral Connectivity Index between US and partner i in year t. It measures the level of connectivity in liner shipping between the two countries (partners). The data is obtained from the UNCTAD statistical portal (https://unctadstat.unctad.org).
- $ExchangeRate_{it}$: The exchange rate between the local currency of partner i and the

US dollar, measured as the local currency per US dollar. The exchange rate is based on the value in 2005 as the base, with $ExchangeRate_{i2005} = 100$. If the exchange rate decreases, it indicates a depreciation of the US dollar. The data is obtained from the World Bank database "World Development Indicators (WDI)" (worldbank.org).

- $GDP\ per\ capita_{it}$: the per capita Gross Domestic Product (GDP) of partner i in year t. The data is obtained from the UNCTAD statistical portal.
- μ_i: the partner-fixed effects, which capture the time-invariant characteristics of partner i, such as distance from US, common language, contiguous borders, and continent.
- ρ_t: the year-fixed effects.
- ε_{it}: error term.

Table 3.2.1 The classification of service trade

Sub-categories	Components
Commercial service	Manufacturing services on physical inputs owned by others Maintenance and repair services not included elsewhere (n.i.e) Construction Insurance and pension services Financial services Charges for the use of intellectual property n.i.e. Telecommunications, computer, and information services Other business services Personal, cultural, and recreational services
Travel service	Business: Acquisition of goods and services by border, seasonal, and other short-term workers; Other (Business) Personal: Health-related; Education-related; Other (Personal)
Transport service	Sea transport Air transport Other modes of transport Postal and courier services

Note: The initial category of EBOPS 2010 can be found in Table D1.
Source: Manual on Statistics of International Trade in Services 2010.

3.2.4.1 Econometric model

Although the US has signed OSAs with more than 130 countries, which include both developed countries and developing countries, there are other omitted variables that may influence both OSAs and service trade at the same time. Such as the political relationship between two countries or regions, positive bilateral relations and mutual trust can facilitate negotiations and cooperation, increasing the likelihood of signing an OSA and enhancing service trade. However, it is difficult to quantify bilateral relations between two countries, making it challenging to include it as a control variable. There may also be bi-directional causality. The signing of an OSA could promote the growth of service trade because it enables cheaper and more convenient air transportation, thereby facilitating cross-border service exchanges and trade. However, the simultaneous growth in service trade can also create momentum or provide motivations for US to sign OSA, as airlines and related stakeholders may advocate for negotiations between governments to gain more business opportunities.

Due to the endogeneity issues mentioned above, our baseline gravity-type regression model is unable to establish a causal relationship between OSA and service trade. To address this issue, we employ an Instrumental Variable (IV) approach. The IV we utilize is the number of common cities in other countries with direct flights from both the US and partner country or region i. $Common\ city\ number_{it}$ is a valid IV because it is correlated with OSA but unrelated to service trade. If there are more common direct cities in other countries with air connections to both the US and partner country, these two countries have a greater incentive to sign an OSA, which would further promote direct air connections between them. However, the common city number with other countries will not directly affect the service trade between the US and the partner country.

A two-stage least squares estimation is employed to investigate the impact of OSA on service trade. The first-stage regression equation is as follows:

$$OSA_{it} = \alpha_2 + \beta_2 \times \ln\ Common\ city\ number_{it} + \boldsymbol{G}'\boldsymbol{X}_{it} + \delta_i + \eta_t + \theta_{it} \qquad (3.2.2)$$

The second-stage regression equation is specified as follows,

$$\ln Y_{it} = \alpha_3 + \beta_3 \times \widehat{OSA_{it}} + \boldsymbol{\Gamma}'\boldsymbol{X_{it}} + \vartheta_i + \iota_t + \kappa_{it} \qquad (3.2.3)$$

Equation (3.2.3) estimates the causal effect of OSA on the US's bilateral commercial, transport, and travel service trade with a consistent estimator of β. The model includes the exogenous control variables $\boldsymbol{X}_{it}$, as well as time and country fixed effects, in both the first-stage and second-stage regressions to control for potential confounding factors and ensure a robust estimation of the OSA's impact on service trade.

3.2.4.2 Data and variable constructions

The primary objective of this study is to investigate the impact of OSA on the bilateral service trade of the US. The WTO Stats database is the main source of service trade data. The database contains the US's annual service trade data with each of the 202 partner countries/regions/islands for the period since 2005. The service trade data is categorized into three types, namely commercial, travel, and transport, as explained in Table 3.2.1. The estimation is conducted separately for each of these subcategories. Our data period spans from 2005 to 2019, with the exclusion of data after 2019 due to the significant negative impact of the pandemic on international flights and service trade (Shingal, 2024; Sun et al., 2020). To mitigate the impact of outliers on the data, we applied a 5% winsorization to the service trade data. As a result, we excluded those countries with a total service trade value of largely less than 10 million US dollars in imports and exports with the US. Ultimately, our final sample consists of 191 partner countries. Among these 191 partners, 126 have signed the OSA with the US during the study period. Figures D1 and D2 depict the trend of service trade exports and imports between the US and its top 10 partner countries. In the US's service trade exports, the largest service trade partners are Canada and the UK. They maintain a significant trade relationship with the US, engaging in various sectors such as finance, professional services, and tourism. Additionally, Japan, Ireland, China, Germany, Switzerland, Mexico, South Korea, and the Netherlands are also key service trade export partners for the US. In terms of service imports, apart from the aforementioned countries, Bermuda, India, and France play important roles as service trade import partners for the US. France primarily contributes to the field of transportation services, while India and Bermuda are significant sources for commercial service imports.

OSA data for the US is compiled from the official website of the US government.[31]

[31] The data is from https://www.state.gov/civil-air-transport-agreements.

By 2023, the US has signed OSAs with 136 partners. Figure 3.2.5 shows the geographical distribution of 134 partners (with the except of Netherlands Antilles and Chinese Taipei), with the US being represented in red. During our data period, the US signed OSAs with 129 partners by September 2019. Among these 129 partners, there are 3 that have no service trade data with the US, which are the Netherlands Antilles, the Cook Islands, Bonaire, St. Eustatius, and Saba.

To construct the IV, $Common\ city\ number_{it}$, the aviation data used is sourced from the Cirium schedule database. This database contains flight information among various countries, including details such as the origin airport, destination airport, and the number of scheduled seats. The $Common\ city\ number_{it}$ is defined as the count of cities in other countries that have direct flights between the US and its trade partners[32]. This measure reflects the degree of network overlap and connectivity facilitated by other countries. The inclusion of third-party countries' common cities with direct flight as an IV is justified by the assumption that the presence of direct flights between the US, its trading partners, and other countries reflects stronger economic ties and connectivity. The number of common direct flight cities serves as a proxy for the level of economic integration and interdependence between these countries.

Control variables have been explained in the former section. The descriptive statistics of the variables are given in Table 3.2.2. As shown in Table 3.2.2, the average amount of service export between the US and 191 partners is 3403 million USD, while the average service import is 2625 million USD. Among them, commercial service trade accounts for more than 60% of total service trade. The US incurs an overall trade surplus with its trading partners. Also, the average internet penetration rate is 40% of the population, which is calculated as the percentage of the population that uses the internet. The average GDP per capita in the US's partner country is 14.6 thousand USD per year. The average common city number between the US and its partners is 25. This indicates a significant level of connectivity and network overlap between these countries, facilitating direct air travel and promoting economic ties.

[32] In our calculation, we do not differentiate between airports and cities, assuming that one airport represents one city. Although there are a few cities with multiple airports, this does not significantly impact our conclusions.

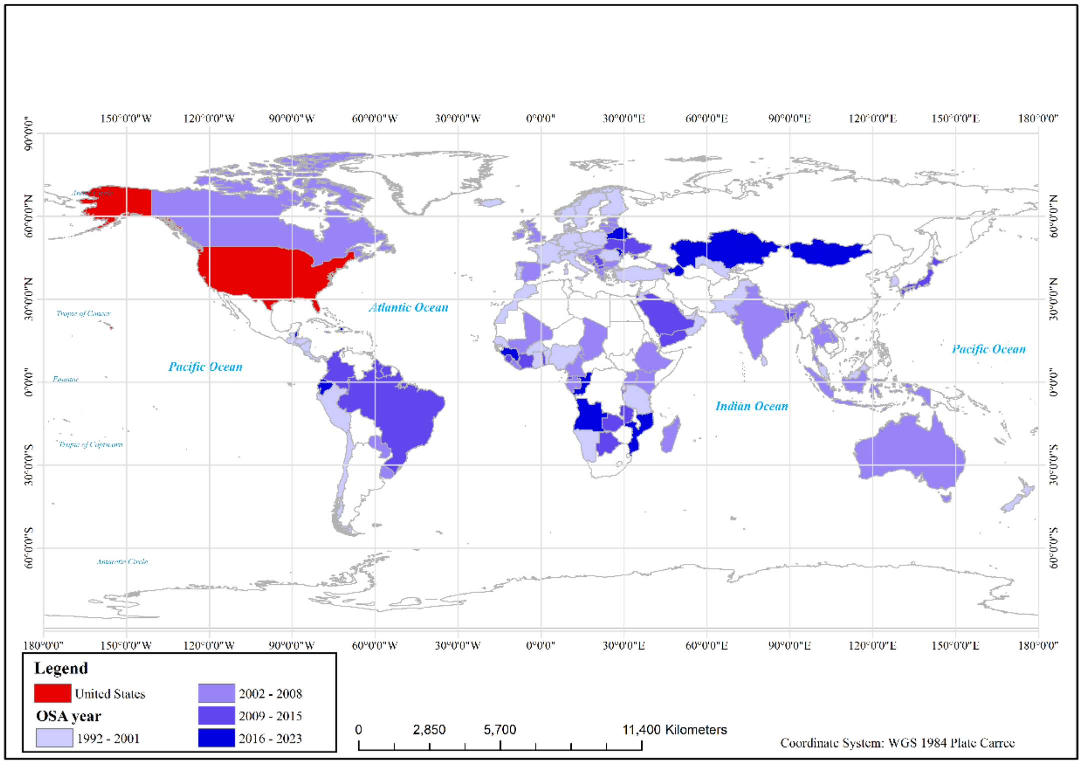

Fig. 3.2.5: Geographical distribution of OSA partners of the US (US in red)
Notes: This figure illustrates the distribution of 134 OSA partners of the US. Lighter colors indicate earlier years of signing the OSA.
Sources: Compiled by authors based on the data from the US government and Esri (https://www.state.gov/civil-air-transport-agreements, www.esri.com).

Table 3.2.2 Summary statistics

Variable	Obs	Mean	Std. Dev.	Unit
Commercial Export	2295	2281	6291	Million USD
Transport Export	2295	530	1290	Million USD
Travel Export	2295	810	2580	Million USD
Commercial Import	2295	1762	5803	Million USD
Transport Import	2295	569	1407	Million USD
Travel Import	2295	561	1403	Million USD
OSA	2295	0.575	0.494	Dummy variable
RTA	2295	0.078	0.268	Dummy variable
Internet penetration	2295	39	30	Percent
LSBCI	2295	0.211	0.122	Unit
Exchange Rate	2295	120	151	Foreign currency per USD
GDP per Capita	2295	14958	20297	USD
Common city number	2295	26.575	25.071	Unit

3.2.5 Estimation Results and Discussions

This section reports the estimation results of 2SLS regression as specified in Section 3.2.4 (see subsection 3.2.5.1). In addition, the lead and lag effects of OSA on service trade are also examined as a robustness check and for additional insights (see subsection 3.2.5.2).

3.2.5.1 The impact of OSA on US bilateral service exports and imports

Table D2 shows the first-stage regression results, indicating constructed IV significantly affects the US's OSA signing. Specifically, the results indicate that for every 1% increase in the common city number between the US and a trading partner, the probability of these two countries signing an OSA increases by 5.6%. Additionally, the first-stage regression yields an F-value of 10.1, indicating the strong relevance between IV and OSA signing.

Table 3.2.3 reports the regression results of OSA on the US's bilateral service trade exports. It can be seen that OSA has a significant positive effect on transport and travel exports, with the impact on travel exports being more significant. However, the impact on commercial exports is insignificant. Table 3.2.4 reports the regression results of OSA on the US's bilateral service trade imports. Also, OSA has a significant positive impact on service trade imports (commercial, travel, and transport), where the impact on commercial imports is the largest. We also discovered that OSA has a more substantial effect on travel and transport service exports compared to imports (as indicated by the larger coefficient for exports). OSA has a more direct impact on travel and transportation service trade in terms of imports and exports. By increasing air connectivity, the signing of OSA can stimulate the development of the tourism industry and facilitate travel and personnel exchanges between the two countries. The coefficients of OSA impacts on service imports and exports are summarized in Figure 3.2.6.

It is interesting to observe that OSA has a significant impact on commercial service imports, while its impact on commercial service exports is not statistically significant. This phenomenon could be attributed to the US's dominant position in the commercial service trade sector. Whether or not OSA is signed does not significantly affect the US's service trade exports to its trading partners. However, OSA does influence the US's service imports. This discrepancy may be explained by the fact that the US has already established a highly advanced commercial service export sector over the past few decades, including the establishment of business subsidiaries abroad and the provision of financial and insurance services, among others. As a result, the promotion of commercial service exports through OSA has relatively limited effects. On the other hand, in the case of commercial service imports, the US leverages the signing of OSA to enhance air connectivity, facilitating imports of services from partner countries. To validate our explanation, we present a comparison of US commercial service imports and exports with OSA and non-OSA countries in Figure D3. The figure demonstrates that both OSA and non-OSA countries experienced an increase in US commercial service exports from 2005 to 2019. However, it is evident that OSA countries exhibited a higher growth rate in commercial service imports compared to non-OSA partners. This finding aligns with our regression results, where OSA has a significant impact on commercial imports but not on commercial exports.

To further explore, we conducted an analysis of each of the nine subsectors of commercial services listed in Table D1. The average ratio of each subsector within the commercial service exports imports among the 136 sample partner countries is presented in Table D3. It can be observed that, in the case of commercial service exports of the US, apart from “Other business services” which accounts for 37% of the total, the subsector “Charges for the use of intellectual property” plays a major role, representing over 29% of the total. The export competitiveness associated with the utilization of intellectual property appears relatively weak. Even in cases where countries have not signed the OSA with the US, they often compelled to import the rights to use intellectual property from the US. Consequently, given that these commercial activities do not involve significant cross-border movement of people, the impact of the OSA on commercial service exports is considered insignificant in this context. However, when looking into the commercial service imports of the US, the subsectors “Insurance and pension services” (13%), “Financial services” (13%), “Charges for the use of intellectual property” (16%), and “Telecommunications, computer, and information services” (13%) show relatively even proportions. Enhanced air connectivity between the US and partner countries will facilitate the promotion of services imports from these nations or the outsourcing of services. The impact of the OSA on each commercial service subsector’s exports and imports regression results are also presented in Tables D4(a) and (b). The results indicate that, apart from the charge for the use of intellectual property, OSA significantly influences all other commercial imports. However, OSA only affects the exports of maintenance, financial services, and telecommunications.

Another explanation could be that when the US Department of Transportation (DOT) and Commerce Department negotiate OSAs with foreign governments, they focus solely on air transportation without considering trade. However, enhanced air transportation significantly facilitates trade. Reduced airfares resulting from OSAs can promote information exchange, facilitate movement of people among countries, connect more cities, and ultimately lead to the US importing cheaper services.

The internet penetration and GDP per capita of partners also have significant positive impacts on commercial, transport, and travel imports and exports. The exchange rate has a significant negative impact on the US's commercial service and travel service exports. In other words, as the exchange rate rises, the cost of US services increases in partner countries, reducing the competitiveness of US exports. Consequently, this can lead to a decline in US commercial export volumes. The impact of exchange rates on commercial and transport service imports is insignificant, but for travel service imports, the effect is negative. When the exchange rate increases, and the US dollar appreciates, the cost of purchasing services from abroad decreases in US dollar terms. As a result, the amount of US dollars required to purchase the same services decreases, and the total spending on these services is reduced. The insignificant impact of exchange rates on commercial and transport service imports may be attributed to the US's strong position in service trade imports. Due to the country's economic influence and market size, the demand for service imports, particularly commercial and transport services, is less sensitive to exchange rates.

Table 3.2.3 The impact of OSA on service exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA	0.568	2.610***	3.267***
	(0.658)	(0.906)	(1.217)
RTA	0.002	-0.204**	-0.212*
	(0.051)	(0.099)	(0.115)
LSBCI	0.518	0.117	0.566
	(0.366)	(0.685)	(0.848)
ln Internet	0.092**	0.184***	0.320***
	(0.041)	(0.054)	(0.073)
ln Exchange Rate	-0.104**	-0.018	-0.255***
	(0.044)	(0.064)	(0.085)
ln GDP per Capita	0.552***	0.575***	0.765***
	(0.064)	(0.098)	(0.124)
Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Notes:
1. The table reports the second-stage regression results on service exports from equation 3.2.3.
2. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. FE = fixed effect.
3. Time-fixed variables, such as distance, contiguous, and common language, can be controlled by the time-fixed effect. Thus, we do not include these variables in our regression analysis.
4. Although the US has signed the OSA with 126 partners, we excluded the 55 partners that do not have direct flights to the US and conducted the regression using the remaining 71 OSA countries and other 65 non-OSA countries. This approach helps to minimize bias and provides a more accurate analysis of the relationship between OSA and the service trade.

Table 3.2.4 The impact of OSA on service imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA	6.095***	2.052**	2.814**
	(2.177)	(0.999)	(1.220)
RTA	-0.342	-0.055	-0.122
	(0.226)	(0.089)	(0.111)
LSBCI	-3.441*	0.172	-0.519
	(1.803)	(0.669)	(0.825)
ln Internet	0.391***	0.186***	0.312***
	(0.141)	(0.066)	(0.075)
ln Exchange Rate	-0.054	-0.049	-0.360***
	(0.176)	(0.072)	(0.077)
ln GDP per Capita	0.908***	0.491***	0.546***
	(0.240)	(0.105)	(0.110)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Notes: The table reports the second-stage regression results on service imports from equation 3.2.3. Other notes are the same as Table 3.2.3.

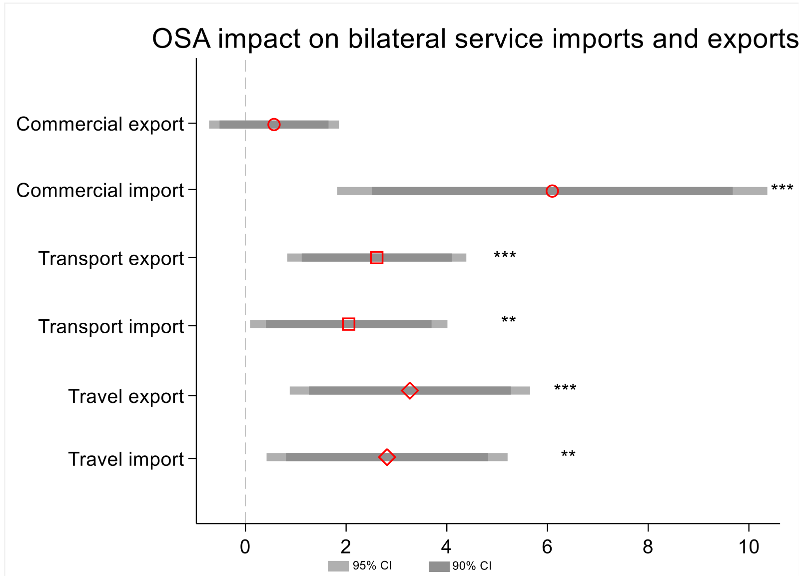

Fig. 3.2.6: The coefficients of OSA on service exports and imports
Notes: The figure shows the estimated OSA impact on US bilateral service exports and imports. The coefficients are compiled from Tables 3.2.3 and 3.2.4.

3.2.5.2 The OSA lead and lag impacts on US bilateral service exports and imports

In the previous section, we identified the significant positive impact of OSA on service trade imports and exports. However, the OSA negotiation process among countries often spans several years. This raises an interesting question: Does OSA have a lead effect, where markets and firms anticipate the agreement and adjust their strategies accordingly, even before the agreement is finalized? The "lead effect" can be understood as the anticipated positive impact that is expected to occur following the signing of the agreement, and this impact may begin to manifest even before the agreement officially takes effect. On the other hand, there may also be a lag effect, as service trade imports and exports involve complex supply chains and information dissemination, and consumers and firms may require time to respond to the signing of OSAs between two countries. In this section, we aim to identify the lead and lag effects of the OSA and determine the specific lead and lag years associated with these effects, which is our main contribution.

In the regression analysis, we introduced additional variables to capture the lead and lag effects of OSA. Denote the OSA signing year of the US and partner i as t_i^*. To capture the lead effect of OSA, we defined the variable $OSA\ lead\ 1\ year_{it} = 1$ when $t \geq t_i^* - 1$. The coefficient of this variable indicates whether OSA has a one-year lead impact before its official signing. Similarly, $OSA\ lead\ 2\ years_{it} = 1$ since $t \geq t_i^* - 2$. To capture the lag effect of OSA, we defined the variable $OSA\ lag\ 1\ year_{it} = 1$ until $t \geq t_i^* + 1$. $OSA\ lag\ 2\ years_{it} = 1$ until $t \geq t_i^* + 2$. We included the variables capturing the lead effects of OSA for two years and the lag effects for four years in our model separately. The complete regression results of each lead and lag year are reported in Appendix D2. We have reorganized the coefficients of the OSA in Tables 3.2.5 and 3.2.6. Table 3.2.5 reports the impact of OSA lead and lag terms on service trade exports, while Table 3.2.6 reports the impact on imports. From Tables 3.2.5 and 3.2.6, we observed a one-year lead effect and three-years lag effects. In line with the findings presented in Tables 3.2.3 and 3.2.4, the lead and lag effects of OSA have an insignificant effect on commercial exports. However, there are significantly positive impacts on transport exports, travel exports, commercial imports, transport imports, and travel imports. The coefficient of OSA (signing year) is consistent with that shown in Tables 3.2.3 and 3.2.4, and we have replicated it here to facilitate a more effective comparison.

The significant positive one-year lead effect and three-year lag effect can be explained as follows, during the negotiation stage, market participants in partner countries, such as airlines, tourism operators, and freight companies, may anticipate the market opening in advance and start to adjust their business strategies to prepare for the new market conditions. But such anticipations will not take place too soon. It only has a significant impact before one year of the official application of the OSA. Regarding the lag effect, once the OSA is officially implemented, airlines need time to allocate aircraft to new routes or frequencies. We observed a gradual increase in the coefficients of "OSA lag 1 year", "OSA lag 2 years", and "OSA lag 3 years". This indicates that the positive impact of OSA does not occur immediately but takes several years to manifest, with the impact progressively growing over time. After three years of increasing impact, the OSA has fully influenced the service trade, reaching a new state of sustained growth since its signing. It is interesting to note that the estimated coefficient of the lead one-year impact is the largest, indicating that airlines or related companies may have overreacted one year before the official signing of the OSA. With the official signing, these companies gradually adjust their strategies.

To better understand the lead and lag impacts we quantified, Figure 3.2.7 illustrates the trend of average service trade exports and imports from the US to 8 OSA countries that signed the OSA in 2010 and 2011 before and after the signing of the OSA. In Figure 3.2.7, it is evident that there is a significant increase in service trade even before the OSA signing (horizontal axis = -2). This observation aligns with our empirical findings, where the coefficient of the one-year lead impact is the largest. Furthermore, in the three years following the OSA signing, service trade continues to grow steadily, reaching a new equilibrium. In the fourth year and onwards, the growth rate slows down, indicating a transition into a more stable phase. The reason for selecting the eight countries that signed the OSA in 2010 and 2011 is to demonstrate the trends in the five years prior to the agreement and the eight years following it. Additionally, when considering the trends of countries that signed the OSA in other years, we find that they exhibit a similar pattern to Figure 3.2.7.

Table 3.2.5 The lead and lag effect of OSA on service export

	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lead 2 years	2.181	9.545	12.792
OSA lead 1 year	0.819	3.748**	4.749**
OSA	0.568	2.610***	3.267***
OSA lag 1 year	0.583	2.669***	3.345***
OSA lag 2 years	0.629	2.862***	3.603**
OSA lag 3 years	0.764	3.446**	4.380**
OSA lag 4 years	1.586	7.271	9.163

Notes:
1. This table reports the estimated OSA lead and lag effects on US service exports.
2. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
3. The complete results of IV regression for each lead and lag effect, including control variables, are shown in Appendix B.

Table 3.2.6 The lead and lag effect of OSA on service import

	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lead 2 years	35.586	9.483	10.779
OSA lead 1 year	9.682*	3.100*	4.074*
OSA	6.095***	2.052**	2.814**
OSA lag 1 year	6.125***	2.091**	2.879**
OSA lag 2 years	7.172**	2.246**	3.095**
OSA lag 3 years	7.711**	2.744*	3.766**
OSA lag 4 years	15.399	6.004	7.927

Notes: This table reports the estimated OSA lead and lag effects on US service imports. Other notes are the same as Table 3.2.5.

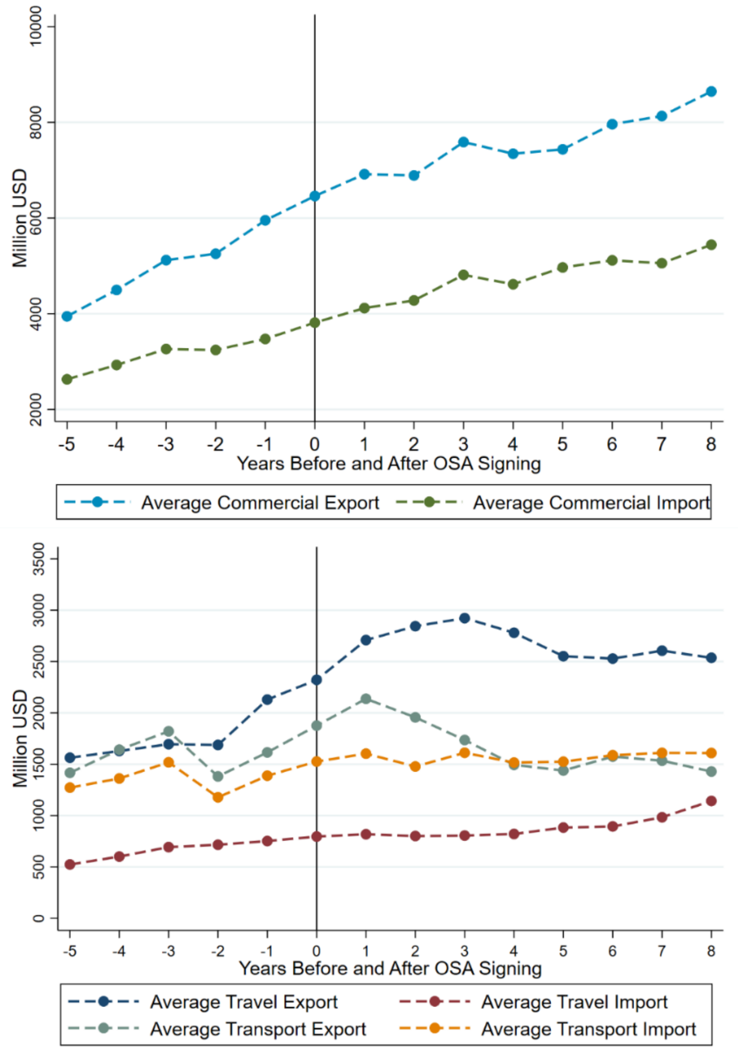

Fig. 3.2.7: Trend of Average US service trade exports and imports with 8 OSA countries (OSA signing year: 2010,2011)

Notes: This figure shows the trend of US bilateral exports and imports before and after the OSA signing. To ensure data consistency and comparability, we specifically chose a sample of 8 countries that signed OSA with the US in 2010 and 2011. In order to highlight the trends more clearly, commercial service trade and transport/travel are presented in separate graphs.

Source: Compiled by authors based on the data from WTO Stats portal.

3.2.6 Mechanism Analysis

This section investigates the mechanism by which the OSA influences service trade through an analysis of air connectivity between the US and its partners. Section 3.2.6.1 examines the impact of OSA on air connectivity, while Section 3.2.6.2 empirically explores the relationship between air connectivity and service trade.

3.2.6.1 The impact of OSA on air connectivity

The OSA aims to eliminate government intervention in international air transport services, liberalize the aviation market, increase flight frequency, and reduce airfare costs. These objectives suggest that the signing of OSAs among countries primarily influences air connectivity between them. Piermartini and Rousová (2013) studied 2,300 Air Services Agreements covering 184 countries, examining the impact of air services liberalization on passenger flows. Their findings suggest that OSAs could increase global passenger traffic by approximately 5%. This implies that OSAs have the potential to significantly boost international travel and connectivity.

In this study, we use the number of cities in partner countries that have direct flights from the US, $Direct\ City_{it}$, and the number of average seats per direct city, $Average\ Seats\ per\ City_{it}$, to measure the air connectivity between the US and partner countries. These two variables capture different aspects of air connectivity. The number of direct cities measures the accessibility of air connections between two countries. The average seat number per direct city measures the route density and available capacity between two countries. Figure 3.2.8 shows the mechanism of the impact of OSA on service trade through air connectivity, which we will identify in this section. The equations are identified in Equations 3.2.4 and 3.2.5. Control variables remain the same as Section 3.2.5.

$$\ln Direct\ City_{it} = \alpha_4 + \beta_4 \times OSA_{it} + \mathbf{K}'\boldsymbol{X_{it}} + \lambda_i + \nu_t + \xi_{it} \quad (3.2.4)$$

$$\ln Y_{it} = \alpha_5 + \varrho \times \ln Direct\ City_{it} + \mathbf{M}'\boldsymbol{X_{it}} + \varsigma_i + \varphi_t + \phi_{it} \quad (3.2.5)$$

Due to the endogeneity issue between OSA and air connectivity, which means the signing of OSA will improve the air connectivity, while on the other hand, the air connectivity may also influence the motive for signing OSA, we reported the regression result of Equation 3.2.4 in Appendix D3, Table D11. Table D11 shows the significant positive impact of OSA on air connectivity, both average seats per city and direct city number.

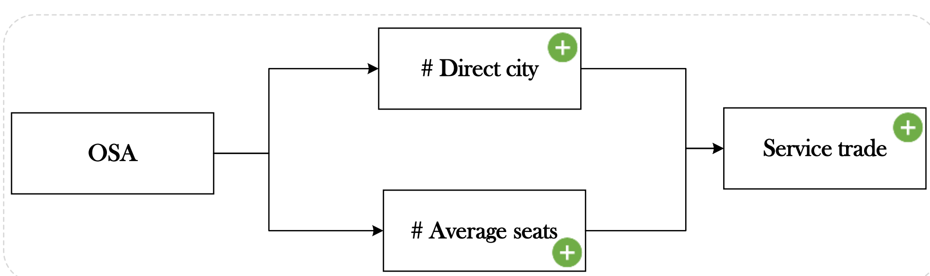

Fig. 3.2.8: The mechanism of the impact of OSA on service trade

3.2.6.2 The impact of air connectivity on bilateral service trade

In this section, we conducted an empirical analysis to examine the impact of air connectivity on service trade to verify Equation 3.2.5. This empirical regression, however, suffers from endogeneity issues. There are omitted variables that influence both air connectivity and service trade, such as political relations and economic ties between the two countries. Controlling these influences through control variables is challenging. To address this endogeneity problem, we employed an IV approach.

Given the presence of two endogenous variables, namely the number of direct cities and the number of average seats per city, we required at least two IVs to resolve the endogeneity issues. In addition to the common city number from other countries used in Section 3.2.5, which measures the potential connection between these two countries, we defined another IV similar to Oum et al. (2024). This IV is the average number of connecting cities in other countries of two trading countries, $Average\ Connect\ City\ Number_{it}$, which measures the extent to which these two countries are connected to the global aviation network. It can also be interpreted as a measure of the countries' aviation openness. This IV satisfies both the relevance and exogeneity requirements, as a higher number of connecting cities in third countries indicates extensive air connectivity within each country, increasing the likelihood of air connectivity between them. However, this IV does not directly influence the service trade between the two countries. The first-stage regression results, presented in Table D12, show an F-statistic close to 10, indicating the validity of the IVs. However, both IVs did not significantly influence two endogenous variables simultaneously. The common city number significantly influences average seats per route, while the average connecting city number significantly influences the number of direct routes.

Tables 3.2.7 and 3.2.8 present the second-stage results of the IV regression, where air connectivity is the independent variable and service trade is the dependent variable. Table 3.2.7 reports the impact of air connectivity on service trade exports, while Table 3.2.8 reports the impact on service trade imports. The two variables used to measure air connectivity between the US and its partner countries, the number of direct cities and the average seat number per direct city, have a correlation of 0.21, suggesting that multicollinearity is not a concern. Table 3.2.7 reveals that direct route number and average seat number do not simultaneously influence service trade exports and imports. The results show that the average seat number has a significant positive impact on US service trade exports, while the positive impact of the number of direct cities is not significant. This could be because US exports to its trading partners are concentrated in major cities, particularly commercial exports. As the US has already established air connections with major cities in its trading partner countries, adding new city connections may not significantly boost service trade exports. However, increasing capacity can significantly promote US service trade exports, suggesting that increased capacity facilitates people's movement, thereby stimulating service trade exports. Table 3.2.8 shows that, unlike exports, the impact of average seat number and direct city number on commercial, transport, and travel imports differs. Both variables significantly influence commercial imports, indicating that, in the context of importing from trading partners, increasing the number of direct city connections or increasing capacity per city significantly positively impacts US commercial imports. However, for transport imports, only capacity has a significant impact. For travel imports, only the number of cities has a positive impact, suggesting that expanding air connections to more cities in partner countries promotes US travel imports from those countries.

Table 3.2.7 The impact of air connectivity on service exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
ln Average Seats per City	0.174*	0.324***	0.376**
	(0.092)	(0.121)	(0.160)
ln Direct City	0.251	0.727	2.108
	(0.722)	(1.274)	(1.590)
RTA	0.010	-0.156	-0.128
	(0.059)	(0.095)	(0.111)
LSBCI	0.162	-0.014	-0.274
	(0.614)	(1.048)	(1.296)
ln Internet	0.016	-0.010	0.044
	(0.032)	(0.043)	(0.056)
ln Exchange Rate	-0.188***	-0.260***	-0.480***
	(0.059)	(0.077)	(0.107)
ln GDP per Capita	0.467***	0.239**	0.408***
	(0.073)	(0.113)	(0.141)
Observations	2,293	2,252	2,295
Country FE	Y	Y	Y

Year FE	Y	Y	Y

Notes:
1. This table reports the second-stage regression results of Equation 3.2.5, using two IVs, the common city number and the average connected city number.
2. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. FE = fixed effect.
3. The correlation coefficient between direct city number and average seats per city is 0.26.
4. For convenience, in our study, we do not differentiate between airports and cities, meaning that multi-airport cities are considered as multiple connections.

Table 3.2.8 The impact of air connectivity on service imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
ln Average Seats per City	0.354*	0.348**	0.202
	(0.196)	(0.161)	(0.168)
ln Direct City	5.268**	1.335	4.053**
	(2.453)	(1.408)	(1.746)
RTA	-0.215	0.042	-0.081
	(0.158)	(0.107)	(0.103)
LSBCI	-3.612*	-1.024	-2.683*
	(1.920)	(1.166)	(1.408)
ln Internet	-0.206**	-0.005	0.034
	(0.096)	(0.062)	(0.067)
ln Exchange Rate	-0.319**	-0.230**	-0.412***
	(0.152)	(0.101)	(0.110)
ln GDP per Capita	0.296	0.247*	0.261*
	(0.206)	(0.131)	(0.156)
Observations	2,175	2,220	2,272
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table 3.2.7.

3.2.7 Summary

Service trade plays a vital role in economic development by promoting productivity gains,, driving structural transformation, and enhancing international competitiveness. In particular, service trade items include many sectors critical for a nation for developing post-industrial economy such as intellectual properties, IT and software, financial and insurance, R&D, management consulting, all types of turn-key projects, healthcare, education. etc.

This study examines the impact of OSAs on service trade exports and imports using the US bilateral trade with each of 191 partner countries over the 2005-2019 period. The service trade data is categorized into three sectors: ‘commercial services’, ‘transport services’, and ‘travel services’. This study is the first to identify both the ‘lead effect’ and ‘lag effect’’ of OSAs in service trade research. To address the issue of endogeneity, we employ an instrumental variable (IV) approach. We estimate a gravity trade model using US data spanning from 2005 to 2019.

The study finds that OSAs have significant positive impacts on transport and travel service trades as targeted by the US Department of Transportation (DOT).) On the other hand, OSAs have a significant positive effect on US commercial service imports while being not significant for commercial service export. The reasons why our results show strong positive OSAs impact on commercial service import while being insignificant on commercial service export are as follows: (a) Even before OSA signing, most US commercial service traders were able to travel all over the world despite the high cost of air travel. As a result, there was more significant increase in incoming traffic from the bilateral partners to the US; (b). In addition, as more US traders travel to smaller cities in the partners countries, they were able to find cheaper sources to import from the smaller cities than just importing from the hub cities. (c). The US exports are more concentrated in intellectual property, software financial services, etc. which are less affected by OSAs. Furthermore, the study reveals that the mechanisms through which OSAs influence imports and exports differ. OSAs affect service exports by influencing seat capacity, while the number of direct routes plays a role in influencing service imports.

An important finding is that there exists a significant positive one-year lead effect as well as three-year lag effects of OSAs on bilateral service exports and imports. In our opinion, leaving out lag and lead effects on service trade modeling would be committing an important model specification error which would bias the empirical results.

To the best of our knowledge, this study is the first to comprehensively analyze all service trade partners of the US, examining the impact of OSAs and identifying both the lead and lag effects. By doing so, our research makes a significant contribution to the existing body of literature on service trade analysis. Understanding the temporal dynamics of the OSA’s effects is crucial for policymakers when making OSA policy decisions as the effects may take time to materialize. It is also important for governments to recognize that different channels exist to promote service exports and imports. If the government intends to boost US service exports, it should focus on supporting airlines to increase their capacity on direct routes. There are also important management implications for market participants, including tourism companies, cross-border service companies, and airlines, particularly when considering the lead effect of OSA. Early positioning and strategic planning are crucial for these entities to effectively capitalize on the opportunities emerging in the market.

When we initiated this research, the post-pandemic period data was not available. Given the significant disruptions caused by the pandemic, the future study which includes post-pandemic period data may refine the results of this study. In addition, global trade friction and geopolitical tensions can disrupt supply chains, leading to increased costs and uncertainty in international trade. In the aviation sector, these conflicts may result in restrictions on air travel, impacting both passenger volumes and cargo transport. Future studies could incorporate more comprehensive data to examine the effects of tariff wars and trade disputes.

CHAPTER 4.

IMPACT OF AIR CONNECTIVITY ON MANUFACTURING FIRM EMISSIONS

CHAPTER 4: PREFACE

In the following chapter, I use empirical models to investigate the social benefits of air connectivity from the micro perspective of firm emissions. This chapter will examine the impact of air connectivity on emissions from China's manufacturing firms. In the co-authored study, I take the lead in developing the empirical model, interpreting the results, and drafting the manuscript, while acknowledging the valuable contributions of my co-authors in collecting data and providing guidance.

4.1 Abstract

This study investigates the causal relationship between air connectivity and manufacturing firm emissions in China by matching firm data with city aviation development data from 2005 to 2013. The study focusses on sulfur dioxide (SO_2) emissions, which have significant adverse health effects on the human respiratory, cardiovascular, and nervous systems and contribute to nonaccidental death. An air connectivity index is constructed to how well each city is connected to the aviation network. Using instrumental variable methods, the study finds that a 1% increase in city air connectivity leads to a 0.1% decrease in SO_2 emissions from manufacturing firms. This reduction is facilitated by a more accessible aviation network and more frequent interactions of business travelers. Specifically, the reduction is driven by technological advancements in the production and emission control processes due to increased firm green production efficiency, increased patent applications, and the growth of the scientific research and technical service industry in the city. We use these estimates to quantify the deaths prevented and years of life saved by the improved air quality caused by enhanced air connectivity. These results highlight the potential public health gains achievable by enhancing air connectivity.

4.2 Introduction

The adverse health effects of air pollution have long been investigated. Research has revealed a correlation between exposure to polluted air and premature mortality (Dedoussi et al., 2020; Lelieveld et al., 2015). The continuous exposure to air pollutants, such as fine particulate matter (PM2.5, PM10), sulfur dioxide (SO_2), and carbon monoxide (CO), has been linked to various diseases, such as dementia, respiratory and cardiopulmonary disease, and even lung cancer (Cheung et al., 2020c; Salvo et al., 2024; Sun et al., 2024). Moreover, vulnerable groups such as children, the elderly, and individuals with pre-existing health conditions are particularly susceptible to the adverse effects of pollution (Beatty & Shimshack, 2014; Ferro et al., 2024; He et al., 2016; Wang et al., 2018c).

SO_2 in the atmosphere mainly comes from the combustion of sulfur-containing fuels such as coal, oil, and natural gas. SO_2 is also a precursor gas in the formation of PM2.5 (Lippmann & Thurston, 1996). Oxidant pollutants are considered more significant indicators of health effects compared to particulates (Wong et al., 2001). Although India is overtaking China as the world's largest emitter of anthropogenic SO_2 (Li et al., 2017), China is still the largest user of embodied coal (Wu & Chen, 2018). In terms of energy carriers in China, manufacturing sectors consumed about 38% of the total coal in 2022. Therefore, controlling SO_2 emissions from manufacturing firms will significantly reduce overall SO2 emissions in China.

Regarding firm emission control, the existing literature mainly focused on the role of environmental regulations (Cai et al., 2016; Chen et al., 2018; Greenstone, 2002, 2004; Liu et al., 2017, 2021). In contrast, studies exploring the role of other factors in emissions reduction are relatively limited. Existing research includes topics such as investment tax incentives (Qi et al., 2023), foreign direct investment (FDI), high-speed rail (HSR) (H. Li & Guo, 2021), and trade liberalization (Cui et al., 2016). Additionally, some literature examines the impact of technological advancements on firm emissions reduction (Abid et al., 2022; Cao et al., 2016). An important pathway for improving technology or total factor productivity is through learning and knowledge diffusion. In reality, however, access to knowledge is highly imperfect (Griliches, 1957). Knowledge tends to flow more readily between individuals who are geographically close to one another, as exemplified by the success of Silicon Valley. A long-standing intellectual tradition also posits that face-to-face social networks are crucial drivers of knowledge and information transmission, facilitating knowledge sharing in various ways (Al et al., 2016; Storper & Venables, 2004). Bai et al. (2024) found that decreasing travel time between U.S. cities increases knowledge flow and knowledge diffusion across firm boundaries.

In China, civil aviation has experienced rapid development over the past two decades, with passenger volume rising from 138 million in 2005 to 1.17 billion in 2019. The number of airports also increased from 135 to 238. Through the aviation network, more cities have established air connections. Given that manufacturing firms are major sources of pollutant emissions, an important question arises: will these firms benefit from the knowledge diffusion fostered by air connections and reduce their emissions? This raises important questions: What is the causal impact of aviation development on emissions from manufacturing firms? What is the mechanism behind this impact? What are the health impacts of improved air quality resulting from enhanced connections to other cities?

To explore these questions, we first develop an index to measure city air connectivity, quantified as a weighted count of all destinations accessible via nonstop flight service. We then employed instrumental variable methods to identify the causal impact of air connectivity on firm emissions. Two instrumental variables are similar to the air connectivity index but measure a city's air connectivity under the hypothetical scenario that the city could establish connections with all airports. Similar instrumental variables have been used in prior studies for estimation (Cristea, 2023). Second, we examined the mechanisms underlying this impact, specifically whether firms achieve emission reductions through technological advancements in either the production process or emission control processes. Third, we quantified the health benefits arising from improved air quality due to reduced emissions. The answers to these questions provide critical insights into the potential environmental benefits and health benefits of enhancing air connectivity in China.

We employ three main datasets in our analysis. The first dataset is sourced from the Cirium SRS Analyser, providing global monthly aviation operation data from 2005. This includes information on OD route-level airlines, flight frequency, and scheduled seat data, which we use to construct the air connectivity index. The second dataset combines the Annual Survey of Industrial Firms (ASIF) and China's Environmental Statistics Database

(CESD), offering detailed information on over 170226 manufacturing firms. This includes data on their location, age, assets, industry code, output, and pollution emissions in China from 1998 to 2013. The third dataset is the China Disease Surveillance Points System (DSPS) database, which provides mortality rates for various diseases and age distribution at the time of death, aiding in quantifying the health impact of improved air connectivity.

Our main findings are as follows. We identify a significant negative effect of city air connectivity on firm pollution emissions. Specifically, a 1% increase in a city's air connectivity results in a 0.1% decrease in SO2 emissions from each manufacturing firm within the city. This reduction is primarily attributed to advancements in emission control technology. City air connectivity also significantly reduces industrial gas emissions. While some may argue that this emission reduction could be due to industrial relocation or energy structure upgrades, our analysis shows that city air connectivity does not significantly affect firm output or coal consumption. Regarding air pollution, a 1% increase in city air connectivity is associated with a reduction of 0.170 $\mu g/m^3$ in city SO2 concentration. These findings demonstrate that enhanced air connectivity can effectively mitigate firm pollution and air pollution from a micro perspective. This reduction is facilitated by a more accessible aviation network and the frequent interactions of business travelers. Specifically, it is driven by technological advancements in both production and emission control processes, which result from enhanced firm green production efficiency, an increased number of patents, and the growth of the scientific research and technical services industry in the city.

Next, we explore the heterogeneity in the effects of improved air connectivity on firm emissions across various subgroups. We find that the effects are more pronounced in Eastern China, which is related to the distribution of firms and regional development. The emission reduction effect is also more significant when cities connect to more major domestic cities. This further validates our knowledge transfer mechanism. However, the impact on emission reduction for cities with more connections to international cities is not significantly different from that for cities with fewer international connections. Additionally, connections to more international cities by transfer flights do not have an emission reduction impact. These findings indicate that, at the current stage, manufacturing firms benefit more from connections and innovations in major domestic cities.

We also conducted a calculation to quantify the lives saved from improving air quality. By integrating the World Health Organization's life tables with China's cause-of-death survey dataset, we can more accurately assess the health impacts of improved air quality. Our analysis shows that improved air quality prevented 2772 deaths and reduced years of life lost by 38473 years during the study period in China.

We make three primary contributions to existing literature. First, this study makes a notable contribution to the literature investigating innovation and knowledge diffusion. Most existing research focuses on innovation driven by competition or government policies (Acemoglu et al., 2012; Nesta et al., 2014), but the role of transportation infrastructure has been largely overlooked. The transportation system is a crucial link between cities, facilitating the efficient movement of goods and personnel, fostering economic and employment growth, and enabling global trade (Banerjee et al., 2020; Brueckner, 2003b; Campante & Yanagizawa-Drott, 2018). To our knowledge, limited studies investigated the role of air transport in innovations. Recently, Bahar et al. (2023) have explored the positive impact of direct flights on firm innovation outcomes. Bai et al. (2024) examined the positive impact of decreased travel time—encompassing both driving and flying—on knowledge diffusion. However, both studies only consider flight connections without examining the broader aviation network, including how well a city is connected to other cities and hub cities. Our study constructs an aviation operation network using nationwide flight operation data to calculate each city's connectivity index. We use this to explore the contribution of air connectivity to city and firm development through knowledge diffusion, focusing on firm innovation and the growth of city scientific research and technical services industry. And further investigate its impact on firm emissions. Our study is one of the first to examine the causal effect of aviation development on firm emission reduction through knowledge diffusion and to investigate the underlying mechanisms involved.

Second, this study contributes to the growing body of research focused on controlling emission pollution. Currently, most studies evaluate the direct effects of government environmental regulations. From a market mechanism perspective, scholars have explored the impact of environmental taxes and tradable emission allowances on controlling pollution and fostering environmental innovation (Brunnermeier & Cohen, 2003; Helm, 2003; Lans Bovenberg & de Mooij, 1997). However, there has been limited investigation into the impacts of improved access to more productive or green production markets, which represents an indirect approach to emission control. When a city is well connected to the national innovation network, its firms can benefit from technological advancements in other cities, leading to improved green production efficiency and reduced pollution emissions. This study uses a city's connectivity within the aviation network as a proxy for its connection to the national innovation network and examines the impact of such connectivity on firm green production efficiency, as well as its impacts on firm emissions. Our research fills this gap and provides insights into how improved air connections to major cities or markets can contribute to controlling emissions. We also discuss what types of direct flight connections should be established to maximize knowledge transfer and learning.

Third, this study expands our understanding of the positive impacts of air connectivity on human health and contributes to the literature on the health benefits of air pollution reduction. Numerous studies have shown that air pollution causes various diseases, affects mortality rates, and validates the effectiveness of environmental regulations in reducing mortality (Greenstone & Hanna, 2014). However, our economic analysis links air connectivity with health impacts, concluding that improved air connectivity contributes to lifesaving, reducing years of life lost by 32817 years during the study period. This underscores the critical role of aviation development as a potential tool to reduce the public health burden.

The remaining sections of the study are organized as follows. Section 4.3 provides a comprehensive review of the relevant literature, discussing prior studies related to aviation development and air pollution. Section 4.4 describes the data utilized in this study and presents preliminary summary statistics. Section 4.5 specifies the econometric model and the instrument variables. Section 4.6 reports the estimation results and mechanism analysis. The last section 4.7 presents the conclusions drawn from our study, summarizing the key findings and discussing their implications.

4.3 Literature Review

This study primarily aligns with two strands of literature, with a primary focus on the empirical studies associated with aviation development and air connectivity. The second stream is about the impact of SO_2 on human health.

4.3.1 Empirical models of aviation development and air connectivity

Public infrastructure and regional economic development have been a classic economic research question. Numerous studies have investigated the benefits of public infrastructure for cities, including economic growth, employment growth, industrial development, and more. Recent empirical studies have corroborated the role of commercial aviation in fostering urban development (Lakew & Bilotkach, 2018; McGraw, 2020; Redding et al., 2011; Sheard, 2014, 2021). Brueckner (2003a) conducted a study utilizing US data to examine the causal effects between airline traffic and employment. Through the 2SLS regression, the research revealed that a 10% rise in passenger enplanements within a metropolitan area leads to a roughly 1% increase in employment within service-related sectors. Interestingly, the analysis indicated that airline traffic does not have a discernible impact on employment within the manufacturing and other goods-related industries. In Green's study in 2007, the investigation focused on testing whether the activity levels at airports in metropolitan areas of the US could forecast population and employment growth. Using 2SLS regressions, this study revealed that passenger activity is a powerful predictor of both population and employment growth, whereas cargo activity is not. Blonigen & Cristea (2015) also support the significant positive impact of airline traffic on local population, income, and employment growth in the US. Similarly, Campante and Yanagizawa-Drott (2018) employed regression discontinuity (RD) methods to examine the causal impacts of long-haul direct air connections on business activities at the global level. Their research revealed that air links enhance business connections, indicating that the mobility of people facilitates the flow of capital. Gibbons and Wu (2020) investigated the impact of airports on local economic performance, specifically focusing on the improved access to domestic markets following China's recent airport network expansion. Their findings indicated that the extensive growth of air transport infrastructure in China during the 2000s resulted in significant increases in industrial output, productivity, and GDP, based on analyses using firm-level and county-level datasets.

Although numerous studies have investigated the relationship between air activity and economic and employment growth, there has been relatively little exploration from the perspectives of promoting innovation and environmental economics. One relevant study is by Bahar et al. (2023), which utilized data from 5015 airports worldwide from 2005 to 2015 to examine the impact of nonstop flights on corporate innovation outcomes. Using a regression discontinuity design (RDD) framework, they found that a 10% increase in nonstop flights between two locations leads to a 3.4% increase in citations and a 1.4% increase in the production of collaborative patents between those locations. Building on their research, we aim to further investigate whether direct flight connections in China promote the innovation of emission reduction technologies in manufacturing firms, thereby leading to a decrease in pollutant emissions. We are particularly focused on SO_2 emissions, as coal combustion, a significant energy source for manufacturing firms, produces SO_2, which can affect the human respiratory system and increase respiratory-related mortality.

4.3.2 The impact of sulfur dioxide on human health

SO_2 is a significant gaseous air pollutant and a key component of the broader category of sulfur oxides (SOx). It is one of the six pollutants used to determine the air quality index (AQI), which is a measurement of air pollution levels. Researchers have been investigating the impact of SO_2 on human health for several decades. And they found that SO_2 is associated with asthma, lung cancer, type 2 diabetes, hemorrhagic and ischemic stroke, ischemic cardiac events, missed abortion in the first trimester, and respiratory and cardiopulmonary mortality.

In western European cities, a study by Katsouyanni et al. (1997) found that an increase of 50 μg/m3 in SO_2 or black smoke was associated with a 3% increase in daily mortality. The studies in seven European areas show that SO_2 is associated with asthma admissions in children (Sunyer et al., 2003a) and plays an independent role in triggering ischemic cardiac events (Sunyer et al., 2003b). Chanel et al. (2014) concluded that the implementation of three European Commission regulations to reduce the sulfur content in liquid fuels for vehicles has postponed 2212 deaths per year attributable to reductions in sulfur dioxide in 20 European cities. Kan et al. (2010) investigated the short-term effects of SO_2 on daily mortality using four Asian cities' data and found significant associations between SO_2 and non-accidental and cardiopulmonary mortality. In a recent study, O'brien et al. (2023) investigated the short-term association between SO_2 and mortality using data from 399 cities across 23 countries, spanning the years 1980 to 2018. They concluded that short-term exposure to SO_2 was associated with an excess mortality fraction of 0.50% in these cities. In the research related to China, Chen et al. (2012) using the data in 17 Chinese cities found that an increase of 10 μg/m3 of two-day moving averaged SO_2 was associated with 0.75%, 0.83%, and 1.25% increase of total cardiovascular and respiratory mortality, respectively. Wang et al. (2018c) conducted a nationwide time-series analysis in 272 major Chinese cities from 2013 to 2015. They concluded that a 10 $\mu g/m^3$ increase in the two-day average concentrations of SO_2 was associated with the following increments in mortality: 0.59% from total non-accidental causes, 0.70% from total cardiovascular diseases, 0.55% from total respiratory diseases, 0.64% from hypertension, 0.65% from coronary heart disease, 0.58% from stroke, and 0.69% from chronic obstructive pulmonary disease.

Overall, studies worldwide consistently find that SO_2 has significant impacts on human health. This study aims to link the manufacturing firm SO_2 emission reductions resulting from technological advancements driven by air connectivity to improvements in human health and to quantify the corresponding reduction in human mortality.

4.4 Data

We compile a comprehensive dataset on city air connectivity, detailed firm-level information, and city development data in China between 2005 and 2013. This dataset integrates multiple databases and is rich in both temporal and spatial dimensions, enabling a detailed analysis of how air connectivity impacts pollution emissions from manufacturing firms. This section outlines the data sources and presents descriptive statistics.

4.4.1 Firm-level data

The detailed firm information used in this study is derived from a merged dataset combining the "Annual Survey of Industrial Firms (ASIF)" and "China's Environmental Statistics Database (CESD)" for the period 2005-2013[33]. The industrial sector in ASIF

[33] The most recent data available in these two databases is from 2013. Therefore, our sample only spans from 2005 to 2013. The database follows legal-entity reporting rather than corporate-group reporting, meaning

dataset includes three major categories: mining, manufacturing, and production/supply of electricity, gas and water - with manufacturing accounting for over 90% of the sample. The survey scope of the ASIF includes all state-owned industrial legal entities and non-state-owned industrial legal entities with annual main business revenue of 5 million Chinese yuan or above (raised to CNY 20 million post-2011), consistent with the coverage of the industrial section in the China Statistical Yearbook and the China Industrial Statistical Yearbook. In this study, we focus on manufacturing firms. These databases include the detailed yearly data of manufacturing firms, such as the location, industry category, output, fixed assets, revenues, and SO_2 emissions. Our sample covers 128 cities in China. The merging process involved several steps: first, following the approach of Brandt et al. (2012) and Wang et al. (2018d), we matched the data using firm codes, firm names, and administrative division codes. Second, we conducted an additional matching using firm abbreviations and provincial codes. We also follow the methods of Feenstra et al. (2014) and Yu (2015) to exclude outlier samples and handle missing data.

In Figure 4.1, the average SO_2 emissions of manufacturing firms in China are depicted, illustrating a consistent downward trend from 2005 to 2013. Figure 4.2 illustrates the total SO_2 emissions of manufacturing firms at the city level in 2013, showing an uneven distribution of total emissions. The top five cities in terms of total emissions are Chongqing, Tangshan City and Handan City in Hebei Province, Anyang City in Henan Province, and Suzhou City in Jiangsu Province. Figure 4.3 provides insight into the average SO_2 emissions per manufacturing firm at the city level. It is interesting to observe that while certain cities exhibit high total emissions, the average emissions per firm remain relatively moderate, as exemplified by Chongqing. In Figure 4.3, it is evident that manufacturing firms in western cities exhibit higher average emissions compared to those in the eastern and central regions.

The firm-level data also includes the following variables: firm age, firm size (the number of employees), total fixed assets, type of enterprise, whether the firm is a foreign-owned enterprise, and whether it is state-owned.

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each manufacturing firm is recorded as a distinct observation regardless of parent company affiliations. This ensures that a single firm only appear in one city, but it also has limitations—for instance, the relationships between parent companies and their subsidiaries cannot be captured.

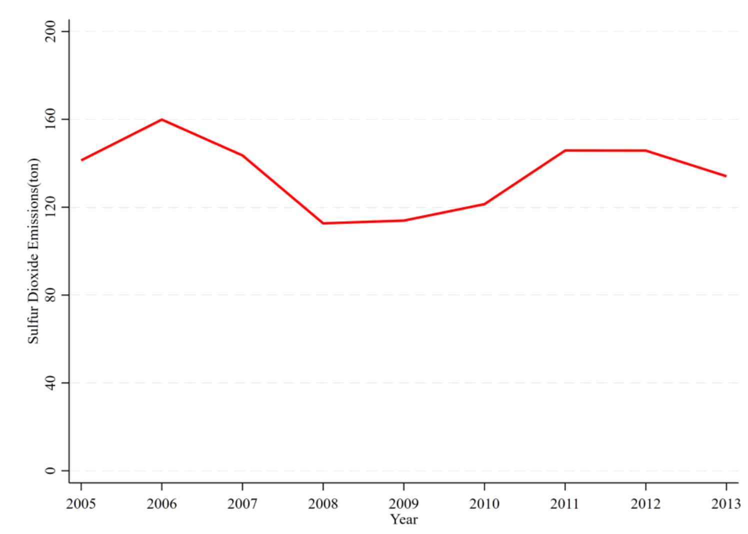


Fig. 4.1: Average SO_2 emissions of Chinese manufacturing firms (2005-2013)

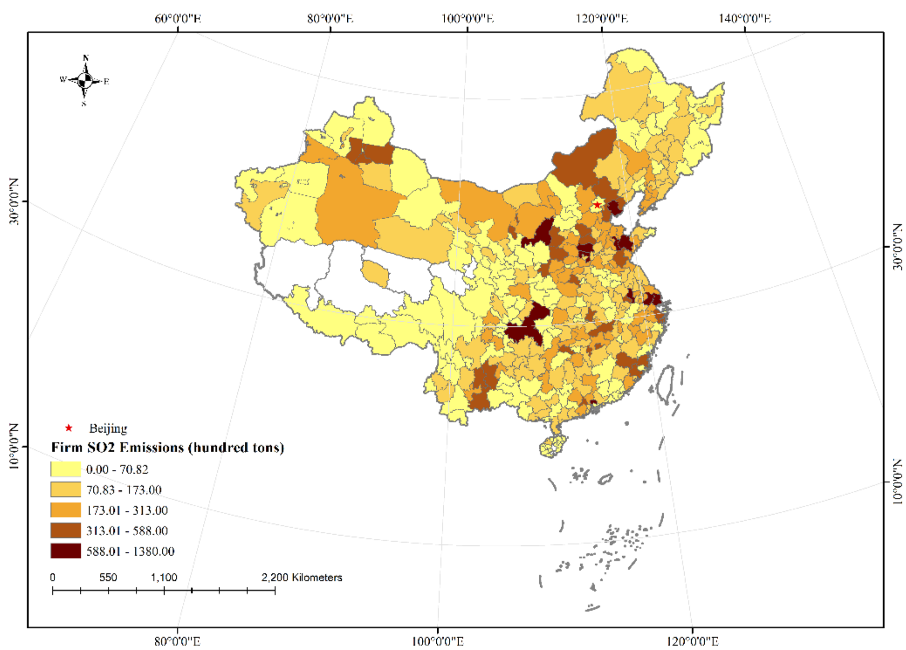


Fig. 4.2: Total SO_2 emissions of manufacturing firms at the city level in 2013

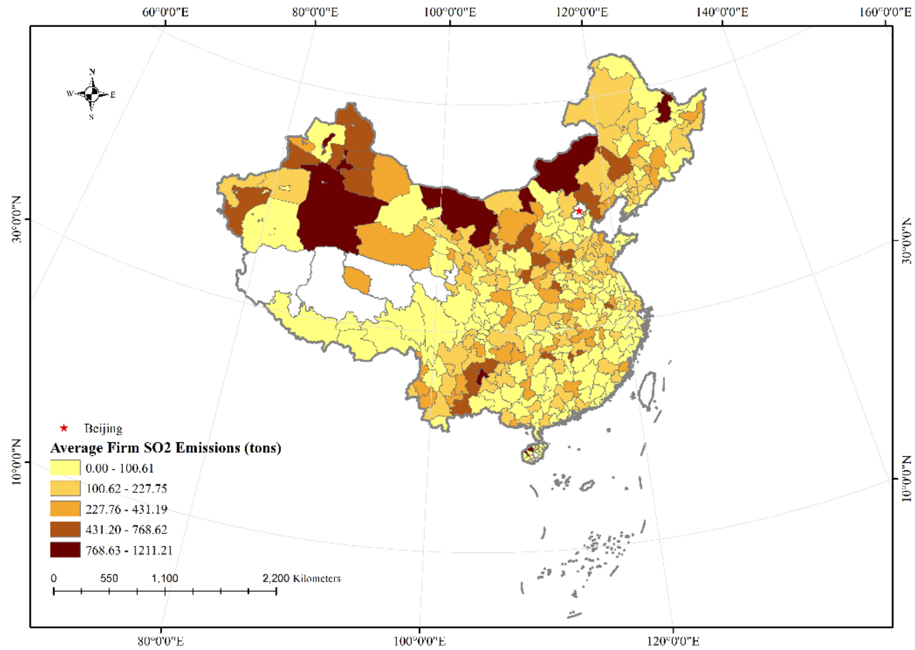


Fig. 4.3: Average SO_2 emissions per firm at city level in 2013

4.4.2 Air connectivity data

The yearly aviation data is obtained from the Cirium Schedule database, which integrates IATA PaxIS and OAG databases. This database contains airline-route-level information in China. Specifically, it includes the operating airline, frequency, scheduled seats, and departure and arrival airports. Our sample covers 136 airports in 127 cities in China. The city-level air connectivity index is calculated using such data as shown in Equation 4.1. We define the air connectivity of city k with the world aviation network as the growth in air traffic resulting from the addition of new flights to both new and existing destinations.

$$Airconnectivity_{kt} = \sum_{d=1}^{N_{kt}} \left(\frac{f_{dt}}{f_t}\right) f_{kdt}^{\frac{\sigma-1}{\sigma}} \tag{4.1}$$

where k and d refer to city and t refers to year. f_{dt} refers to the frequency of all airports in city d in year t (including both domestic and international flights). The values for multi-airport cities are aggregated at the city level. f_{kdt} refers to the flight frequency between city k and d in year t. This air connectivity measure is first proposed by Cristea (2023), which is the sum of all destinations d that city k can access directly by air, with each destination's significance weighted by its connectivity to the whole aviation network. A high value of this air connectivity measure suggests that a city has abundant access to several large hub airports with frequent service. σ denotes the elasticity of substitution between flight departures. Following Cristea (2023), we set σ equal to five. Figure 4.4 shows the average air connectivity of 127 Chinese cities from 2005 to 2013. According to the figure, Chinese city air connectivity experienced rapid growth starting in 2007 onwards. A possible reason could be the 2008 Beijing Olympics. Figure 4.5 illustrates the average air connectivity across different regions, highlighting significantly higher connectivity in Eastern China. Figure 4.6 shows the distribution of air connectivity across various cities in China in 2013. Notably, Beijing, Shanghai, Guangzhou, Shenzhen, and Chengdu ranked as the top five cities in terms of air connectivity.

The city-level control variables, including data on GDP, road density, and high-speed rail (HSR), and the number of enrolled students in higher education institutions, primarily came from the statistical data of the Civil Aviation Administration of China and the "China City Statistical Yearbook." We also included city-level environmental regulation intensity to capture the time-varying impacts of environmental policies or regulations. Following Chen and Chen (2018), we calculated the intensity of city-level environmental regulations based on the number of environmental terminologies found in government reports, such as "environmental protection," "sulfur dioxide," "PM2.5," "emission reduction," "energy consumption," among others. After organizing the data for all cities, we integrated it into a merged dataset comprising the "Annual Survey of Industrial Firms" and the "China's Environmental Statistics Database," using city names as the matching variable. With these steps completed, we obtained the research sample required for this study.

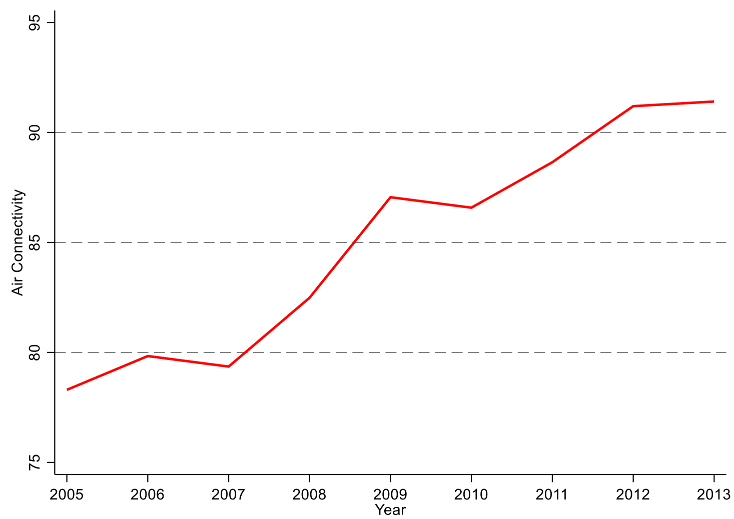


Fig. 4.4: Average air connectivity of Chinese cities (2005-2013)

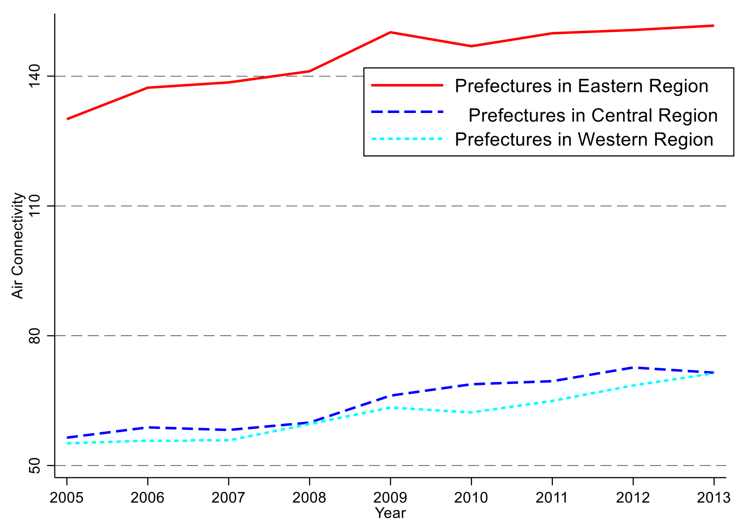


Fig. 4.5: Average air connectivity of Chinese cities across different regions (2005-2013)

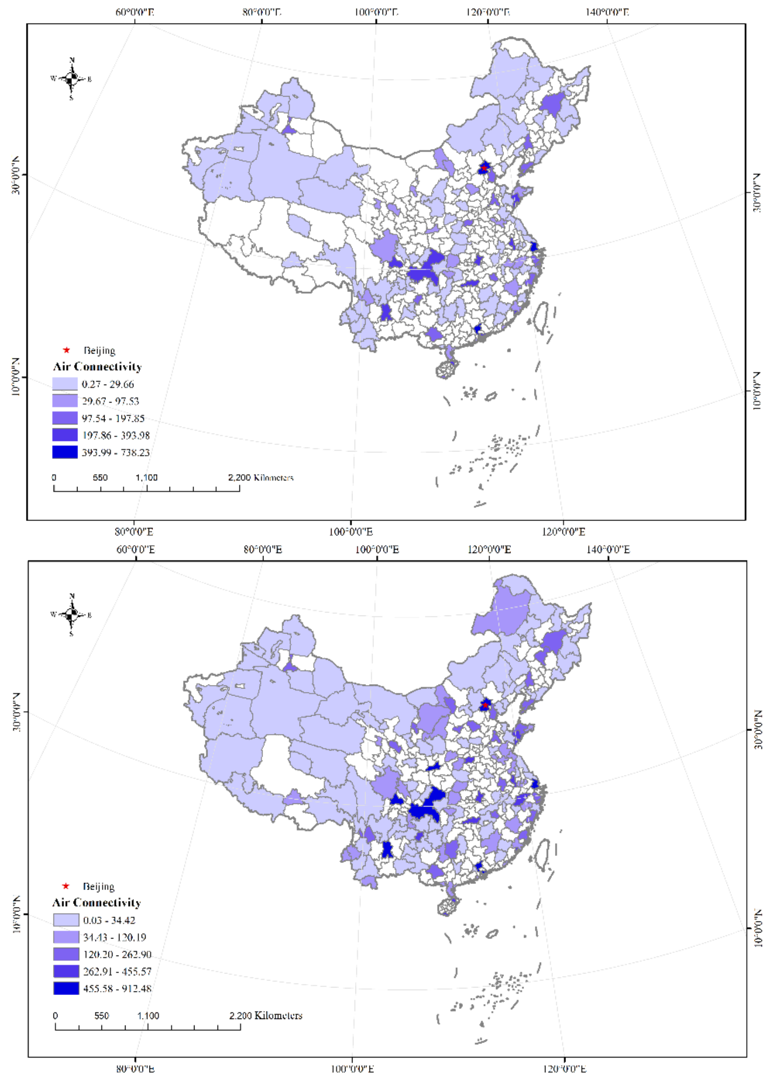


Fig. 4.6: Air connectivity distribution among Chinese cities in 2005 and 2013
Notes: The upper panel is for the year 2005, and the lower panel is for the year 2013. In the map, cities marked with colors are airport cities, with the depth of color indicating the level of air connectivity of the city. Cities shown in white indicate that they do not have airports.

4.5 Empirical Methodology

Our objective is to estimate the causal effect of city air connectivity on firms' SO_2 emissions, net of any potentially confounding factors. There are several identification challenges. The primary challenge is the omitted variables that could affect the air connectivity and firms' emissions together, such as the political environment. We address these econometric challenges by employing an instrumental variable approach, using constructed connectivity variables as two instruments. Following prior studies in the literature explaining the reasons for pollutant emissions (Qi et al., 2023), we employ a linear specification to estimate the relationship between air connectivity and firms' SO_2 emissions.

4.5.1 Panel fixed effects model

We first model the relationship between air connectivity and firms' SO_2 emissions using the following fixed effect panel regression.

$$\ln SO_{2_{ijkpt}} = \beta_0 + \beta_1 \ln Airconnectivity_{kt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \quad (4.2)$$

where i, j, k, p, and t represent firm, industry, city, province, and year, respectively. The dependent variable, $\ln SO_{2_{ijkpt}}$, is firm i's SO_2 emissions in year t, calculated as the natural logarithm of the kilograms of SO_2 emissions plus 1. The independent variable, $Airconnectivity_{kt}$ is the city level air connectivity at year t, quantified in Equation 4.1 to measure the extent to which city k is integrated into the aviation network. Of particular interest is the parameter β_1, which captures the influence of city air connectivity on firm SO_2 emissions. Aviation, recognized as the swiftest intercity transportation mode, plays a pivotal role in fostering city-to-city connections. A well-developed aviation network in a city not only integrates it into the national transportation network but also fosters interpersonal exchanges and knowledge sharing. Our hypothesis posits that a well-connected aviation network in a city is likely to reduce SO_2 emissions from manufacturing firms, possibly through advancements in corporate technologies, enhanced emission reduction efficiency, or lowered pollution outputs.

In addition to air connectivity, firm-level characteristics also influence firm emissions, such as the age of the firm, its size, capital intensity, and whether it is a state-owned firm, denoted by X'_{it} in equation (4.2). Factors at the city level, such as the level of economic development, and transportation infrastructure (including the high-speed rail and highway density), can also impact the development and innovation levels of manufacturing firms, influencing their pollutant emissions, denoted by Z'_{it} in equation (4.2). The variable HSR_{it} equals one if city i has HSR service in year t. Fixed effects are applied for firm, industry-time, and province-time to control for specific attributes. γ_i is a vector of firm fixed effects that account for time-persistent unobserved characteristics affecting firm emissions. Equation (4.2) includes industry-time[34] (η_{jt}) and province-time (ω_{pt}) fixed effects to capture idiosyncratic (but possibly time-varying) emission intensity differentials between particular provinces or manufacturing industries that are independent of city air connectivity. ε_{ijkpt} are the error terms capturing time-varying, firm-specific unobservable variables that may affect firm SO_2 emissions. The error terms may be spatially and temporally correlated. Following Brandt et al. (2017), we clustered standard errors at the city-time level, as the explanatory variables of interest vary at that level, to construct confidence intervals for all models. The detailed definition of control variables and descriptive statistics is in Table 4.1.

As noted above, the OLS estimator of β_1 is prone to being biased for the following reasons: (1). The manufacturing firm is not randomly distributed across the country; (2) emission data may be subject to measurement errors and manipulation. Moreover, air connectivity and SO_2 emissions may be related to unobserved confounding factors. Therefore, a simple linear regression estimate might obscure the true effect of air connectivity on emissions. An instrumental variable model is proposed in the next subsection to deal with this endogeneity issue.

Table 4.1 Descriptive statistics

Variables	Mean	Standard deviation
Manufacture firm SO_2 emissions (ton)	135.7	938.5
City air connectivity (unit)	101	186
Firm level control variables		
Firm age (years)	12.8	10.2
Firm size, number of employee (people)	546	1615
Capital intensity, fixed assets/employee (thousand RMB per employee)	316	5674
Foreign direct investment firm (Dummy variable)	0.204	0.403
State-owned firm (Dummy variable)	0.035	0.183
City level control variables		
GDP (billion RMB)	257.1	275.3
GDP per capita (RMB)	42695	33320
Road density (km/km^2)	1.11	0.466
HSR (Dummy variable)	0.271	0.444

[34] Two-digit industry–time fixed effects are controlled.

Education, higher education enrollment (thousand people)	145	197
Environmental regulation intensity	0.004	0.002
City air connectivity IV1	5488	5498
City air connectivity IV2	2.43	2.95

Notes: Sample size: 255103, including 62563 firms in 285 cities over the period 2005 to 2013. Firm-level variables are reported for each firm per year during the sample period. City-level variables are reported for each city per year during the sample period. A foreign direct investment firm refers to the firm with registration types containing foreign investment. A state-owned firm refers to a firm that is owned, controlled, or partially owned by the government. Road density is the road length per unit area. HSR indicates whether the city has introduced high-speed rail services. The definition of instrumental variables (IV) is provided in equations 4.3 and 4.4.

4.5.2 Instrumental variable model

We address these econometric challenges by using two separate instruments. Following Cristea (2023), we propose two exogenous variables to instrument for city k's connectivity to the national aviation network. These variables closely resemble the functional form of the endogenous air connectivity measure presented in Equation (4.1). The excluded instruments are defined as follows:

$$Airconnectivity\_IV1_{kt} = \sum_{d \neq k} (f_{dt}) \left(\frac{1}{Dist_{kd}}\right)^{\frac{\sigma-1}{\sigma}} \tag{4.3}$$

$$Airconnectivity\_IV2_{kt} = \sum_{d \neq k} (routes_{dt}) \left(\frac{1}{Dist_{kd}}\right)^{\frac{\sigma-1}{\sigma}} \tag{4.4}$$

where d represents all the domestic destination cities available in our sample at year t excluding the origin city i, f_{dt} is the total number of departures from destination city d at year t, and $Dist_{kd}$ denotes the geographic distance between origin city i and destination city d. The second instrument mirrors the previously defined Equation 4.3, utilizing the total nonstop aviation routes (direct routes) from destination city d as a weighting factor ($routes_{dt}$) that reflects the significance of destination d within the aviation network.

To ensure exogeneity, we exclude any data related to the origin city k (except for distance information) from the construction of both instruments. More precisely, when calculating the variable f_{dt}, we exclude the number of flights from destination d to origin city k. Similarly, when calculating the variable $routes_{dt}$, we exclude the air connection from k to d if a direct route between them existed at time t. Also, for exogeneity considerations, we incorporate all domestic destination cities in our dataset in our calculations to guarantee that the pool of potential air connections accessible to origin city k remains unaffected by origin-specific economic factors. This approach ensures that the potential set of air links overlaps with the actual nonstop destinations served from origin city k in year t, thereby establishing the required correlation between the excluded instrument and the endogenous air connectivity variable. The two-stage least-squares (2SLS) estimation is specified as follows. Control variable and fixed effects are the same as in Equation 4.2.

$$1^{st} \text{ stage: } \ln Airconnectivity_{kt} = \pi_0 + \pi_1 \ln Airconnectivity\_IV1_{kt} + \pi_2 \ln Airconnectivity\_IV2_{kt} + X'_{it}\theta + Z'_{kt}\vartheta + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \quad (4.5)$$

$$2^{nd} \text{ stage: } \ln SO_{2_{ijkpt}} = \beta_0 + \beta_1 \ln \widehat{Airconnectivity}_{kt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \quad (4.6)$$

4.6 Econometric Results and Discussion

4.6.1 Baseline results

Table 4.2 reports on the relationship between city air connectivity and firm SO_2 emissions using the OLS estimates. Column 1 reports the baseline results without including control variables while controlling for firm and year-fixed effects. In columns 2-5, we include the control variables and different fixed effects discussed in Equation 4.2. Column 5 reports the results with control variables, firm, industry-year, and province-year fixed effects. Standard errors are clustered at the city-year level. Across all columns, the estimates indicate a significant negative relationship between air connectivity and firm SO_2 emissions. On average, for every 1% increase in air connectivity between a city and the national aviation network, there is a 0.08% reduction in SO_2 emissions from manufacturing firms within the city. This confirms the positive societal impact of air connectivity at a micro level, namely reducing pollution emissions from manufacturing firms. This underscores the essential role of aviation in fostering global environmental sustainability efforts. The HSR is insignificant in column 5, which is consistent with the findings in Gao et al. (2022). They used the firm-level pollution data to examine the impact of HSR from

2002 to 2012 in China and found that HSR has some positive but statistically insignificant effects on both air and water pollution discharge intensities. Additionally, they noted that HSR connections negatively impact discharge intensities in heavily polluting industries. However, the OLS estimates are influenced by various biases, as discussed earlier, limiting their suitability for causal interpretation.

Table 4.2 The impact of city air connectivity on firm SO_2 emissions (baseline OLS estimate results)

Dependent variable: ln SO_2	(1)	(2)	(3)	(4)	(5)
ln Air Connectivity	-0.068***	-0.082***	-0.081***	-0.086***	-0.083***
	(0.023)	(0.026)	(0.026)	(0.027)	(0.026)
ln age		0.126***	0.126***	0.116***	0.114***
		(0.019)	(0.019)	(0.018)	(0.018)
ln size		0.155***	0.150***	0.159***	0.151***
		(0.013)	(0.013)	(0.012)	(0.012)
ln capital intensity		0.056***	0.056***	0.057***	0.056***
		(0.008)	(0.008)	(0.007)	(0.007)
Foreign direct investment		-0.011	-0.016	0.006	-0.001
		(0.050)	(0.049)	(0.049)	(0.048)
State-owned firm		-0.104*	-0.098	-0.119**	-0.108*
		(0.062)	(0.062)	(0.060)	(0.060)
ln GDP		0.201	0.216	0.175	0.156
		(0.282)	(0.258)	(0.262)	(0.246)
ln GDP per capita		-0.250	-0.241	-0.089	-0.068
		(0.299)	(0.274)	(0.282)	(0.264)
Road density		-0.212**	-0.207**	-0.128	-0.108
		(0.096)	(0.099)	(0.149)	(0.148)
HSR		0.017	0.007	-0.012	-0.017
		(0.041)	(0.039)	(0.040)	(0.039)
ln Education		-0.066	-0.064	-0.063	-0.064
		(0.087)	(0.085)	(0.075)	(0.073)
Environmental regulation		-0.277	-0.468	-0.644	-0.174
		(5.856)	(5.857)	(6.025)	(5.958)
Constant	9.247***	8.065***	7.726***	6.702***	6.830***
	(0.052)	(2.409)	(2.269)	(2.295)	(2.222)
Observations	294,529	255,104	255,104	255,103	255,103
Adjusted R-squared	0.785	0.787	0.788	0.790	0.791
Firm fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Industry-year fixed effects	N	N	Y	N	Y
Province-year fixed effects	N	N	N	Y	Y

Note: This table presents the OLS estimated impacts of air connectivity on firm SO_2 emissions. Column 1 displays the estimates without control variables but includes firm and year fixed effects. Columns 2-4 present the estimated results incorporating control variables and various fixed effects. Column 5 reports the results with control variables, firm, industry-year, and province-year fixed effects. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.3 reports the IV estimates of the causal effect of city air connectivity on manufacturing firm SO_2 emissions based on equations 4.5 and 4.6, controlling for firm, industry-year and province-year fixed effects. Columns 1 and 2 present the estimated results using IV1 as the instrument. Columns 3 and 4 report the outcomes using IV2 as the instrument. Columns 5 and 6 show the results using both IVs as instruments. The IV estimates from the first-stage in Table 4.3 are significantly positive (as seen in columns 1, 3, and 5), aligning with expectations. These two IVs are constructed similar to air connectivity but consider the full connections to all cities. The first-stage results are also consistent with the earlier study by Cristea (2023), which defines IV and air connectivity in the same way as this study and also shows the significant positive impact of IVs on air connectivity. The second-stage results, which assessed the causal impact of air connectivity on firm emissions, show a significant negative effect. However, the 2SLS estimates are larger than the OLS estimates (-0.103 vs. -0.084). One possible reason is omitted variable bias, resulting in a negative correlation between the error term in equation 4.2 and air connectivity. Importantly, the IV estimates are expected to correct any endogeneity biases if the proposed IVs are valid, satisfying both the exogeneity and correlation assumptions. Fortunately, this is what is demonstrated in Table 4.3. The first-stage Kleibergen-Paap F-statistics presented in Table 4.3 significantly exceed 10 in all cases, indicating the efficiency of these two IVs; both IVs are significantly correlated with air connectivity. Furthermore, when including both IVs, the p-value of the Hansen J statistic in column 6 is greater than 0.05 (p = 0.103). This fails to reject the null hypothesis that the instruments are orthogonal to the regression residual, suggesting the exogeneity of these two IVs.

Given that the two IVs are constructed in a very similar manner, they exhibit a high level of correlation (correlation coefficient of 0.9). Nonetheless, following Cristea (2023), we still include both instruments in the first stage, as this provides additional information for predicting the endogenous variable, air connectivity. The correlation between the two instruments only affects the efficiency of the estimates, not their unbiasedness and consistency. Therefore, we continue to report the results using both instruments simultaneously in column 6, and we employ both instruments in subsequent estimations.

In column 6, it is shown that for every 1% increase in a city's air connectivity, the SO2 emissions from each manufacturing firm within the city decrease by 0.1%. When converted into absolute emission reductions, a 1% increase in city air connectivity results in a yearly decrease of 135.7 KG in SO_2 emissions per firm. As we aggregate this emission reduction at the city level, the overall emission reduction becomes even more significant. Over the past twenty years, China's aviation network has experienced rapid development and expansion. From 2010 to 2013, the average air connectivity of cities increased by over 47%. When calculating the growth rate of air connectivity per city and estimating the resulting reduction in firm emissions, significant SO_2 emission reductions from 2010 to 2013 are observed in cities such as Huaian, Tianshui, Foshan, Jiayuguan, Fuyang, and Changzhou, with reductions exceeding 3% of the city's industrial SO_2 emissions in 2013. When aggregating the data across all cities, it is revealed that the nationwide emission reduction attributed to aviation connections from 2010 to 2013 totals a substantial 235 thousand tons. This accounts for 1.25% of China's total industrial SO_2 emissions of 18.352 million tons in 2013.

Table 4.3 The impact of city air connectivity on firm SO_2 emissions (2SLS estimate results)

Dependent variables	(1) ln Air Connectivity	(2) ln SO_2	(3) ln Air Connectivity	(4) ln SO_2	(5) ln Air Connectivity	(6) ln SO_2
ln Air Connectivity		-0.152***		-0.075**		-0.103***
		(0.049)		(0.038)		(0.036)
ln AirConnectivity_IV1	0.176***				0.095***	
	(0.015)				(0.012)	
ln AirConnectivity_IV2			1.515***		1.122***	
			(0.064)		(0.073)	
ln age	0.002	0.114***	0.002	0.114***	0.005**	0.114***
	(0.003)	(0.018)	(0.003)	(0.018)	(0.002)	(0.018)
ln size	-0.003	0.151***	0.001	0.152***	0.001	0.151***
	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)
ln capital intensity	-0.002	0.055***	0.003*	0.056***	0.001	0.055***
	(0.002)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)
Foreign direct investment	-0.013**	-0.001	-0.010**	-0.001	-0.013***	-0.001
	(0.005)	(0.048)	(0.005)	(0.049)	(0.004)	(0.048)
State-owned firm	0.010	-0.106*	0.014**	-0.108*	0.010*	-0.107*
	(0.008)	(0.060)	(0.007)	(0.060)	(0.006)	(0.060)
ln GDP	0.633***	0.199	0.173	0.151	0.294***	0.168
	(0.139)	(0.250)	(0.127)	(0.246)	(0.107)	(0.247)

ln GDP per capita	-0.671***	-0.111	-0.198	-0.062	-0.331***	-0.080
	(0.143)	(0.268)	(0.132)	(0.265)	(0.110)	(0.266)
Road density	-0.116**	-0.123	-0.142**	-0.106	-0.106**	-0.112
	(0.045)	(0.148)	(0.057)	(0.148)	(0.045)	(0.148)
HSR	-0.033	-0.020	-0.033*	-0.017	-0.030*	-0.018
	(0.026)	(0.039)	(0.019)	(0.039)	(0.018)	(0.039)
ln Education	0.049	-0.067	0.083***	-0.064	0.102***	-0.065
	(0.034)	(0.073)	(0.026)	(0.073)	(0.027)	(0.073)
Environmental regulation	-6.408	-0.822	2.622	-0.095	1.146	-0.358
	(4.541)	(6.010)	(3.357)	(5.972)	(2.874)	(5.977)
Observations	255,103	255,103	255,103	255,103	255,103	255,103
Firm fixed effects	Y	Y	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y	Y	Y
Province-year fixed effects	Y	Y	Y	Y	Y	Y
K-P rk LM statistic		86.801		136.13		136.69
K-P rk Wald F statistic		143.57		553.38		500.52
Hansen J statistic (p value)		/		/		0.064

Notes: This table presents the two-stage least squares (2SLS) estimated impacts of air connectivity on firm SO_2 emissions. The instruments are defined in equations 4.3 and 4.4. Columns 1 and 2 present the estimated results using IV1 as the instrument. Columns 3 and 4 report the outcomes using IV2 as the instrument. Columns 5 and 6 show the results using both IVs as instruments. Robust standard errors are shown in parentheses and clustered at the city-year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.6.2 Mechanism analysis

This subsection aims to investigate the mechanism behind the negative impact of air connectivity on firm SO2 emissions. One possible mechanism is innovation and knowledge diffusion theory. Arrow (1969) has pointed out that personal interaction is the most significant factor in facilitating the adoption of innovations. Branstetter (2001) further supports the knowledge diffusion effects among firms within the country. A recent study has shown that the geographic mobility of individuals facilitated by nonstop flights boosts the diffusion of knowledge through patent citations and collaboration among inventors, particularly within firms (Bahar et al., 2023). Bai et al. (2024) also examine the causal relationship between proximity and knowledge diffusion, revealing that a decrease in travel time increases knowledge diffusion across firm boundaries. This knowledge diffusion is measured by the number of patent citations between two regions. According to the knowledge diffusion theory, improved air connectivity, linking to more cities through direct flights, facilitates human interaction among firms, which may promote knowledge diffusion and technological advancement in manufacturing firms. This could help manufacturing firms reduce emissions. In this subsection, we will first verify whether air connectivity decreases firm-level output or increases their production technology by investigating its impact on firm value-added output, SO_2 generation, and SO_2 removal. We will then further explore the mechanisms behind these impacts by examining the effect of air connectivity on firm innovation and knowledge acquisition, using firm-level patent application data, firm-level green production efficiency data, and city-level new registration business data.

The impact of air connectivity on SO_2 generation and SO_2 removal

Companies may reduce emissions either by decreasing production levels or implement new pollution mitigation initiatives (Liu et al., 2021). We use the value-added output of a firm to measure its production. Abatement efforts can be categorized into two primary groups: “end-of-pipe” treatments, exemplified by the implementation of flue gas desulfurization units, and “production process modifications,” illustrated by the adoption of advanced, less polluting boilers. With comprehensive data on every production process, we can break down pollutant emissions into the generated amount minus the removal quantity. We use the SO_2 produced before entering abatement facilities as the metric for “production process modifications” abatement, while the amount of removal and the desulfurization capacity are the measures of “end-of-pipe” treatments. After verifying the impact channel of air connectivity on the firm emissions, we further identify the mechanism behind the air connectivity.

To verify the above mechanism, we employ the IV methods to investigate the causal impact of air connectivity on firm output, SO_2 generation, and SO_2 removal. IVs are the same IVs as defined in equations 4.3 and 4.4. The second-stage regression model is specified in equation 4.7.

$$\ln \mathrm{M}_{ijkpt} = \alpha_0 + \alpha_1 \ln \widehat{Airconnectivity}_{kt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \tag{4.7}$$

where M_{ijkpt} refers to four mechanism variables, $SO_2\ generation_{ijkpt}$, $SO_2\ removal_{ijkpt}$, and $Output_{ijkpt}$. Control variables at firm-level and city-level are the same as equation 4.2.

Table 4.4 reports the IV estimates based on equation 4.7. The results in columns 1 and 2 indicate that air connectivity has a significantly negative impact on SO_2 generation and a positive impact on SO_2 removal. This suggests that improved air connectivity not only reduces the SO_2 generation but also increases SO_2 removal and thus decreases the SO_2 emission. The estimated coefficients for firm output are found to be insignificant (as shown in column 3), suggesting that air connectivity had no significant impact on the firm's production levels and did not prompt industrial relocation of manufacturers. The results indicate that manufacturing companies reduce pollution emissions by installing more efficient production facilities that generate less pollution and by enhancing the efficiency of desulfurization facilities to improve pollution removal. From table 4.4, for every 1% increase in air connectivity of the city, without reducing production, the SO_2 generation of manufacturing firms decreases by 0.1%, and the SO_2 removal increases by 0.3%. Our findings are, to some extent, consistent with Liu et al. (2021), who find that China's Key Cities for Air Pollution Control policy effectively lowered SO_2 emissions of manufacturing firms and the main mechanism is from the production process by installing more efficient boilers that generate less pollution. But our study also confirms the innovation in the "end-of-pipe" emission control process by enhancing the desulfurization capacity of facilities.

Table 4.4 Effect of city air connectivity on firm SO_2 generation, SO_2 removal and output (IV)

Dependent variables	(1) ln SO_2 generation	(2) ln SO2 removal	(3) ln Value-Added output	(4) ln coal consumption	(5) Primary industry percentage	(6) Secondary industry percentage	(7) Tertiary industry percentage
ln Air Connectivity	-0.095**	0.337***	-0.003	-0.000	0.172	-0.220	0.045
	(0.038)	(0.127)	(0.014)	(0.034)	(0.118)	(0.194)	(0.153)
Control Variables	Y	Y	Y	Y	City-level	City-level	City-level
Observations	172,086	172,233	112,943	137,983	2,297	2,297	2,297
Firm fixed effects	Y	Y	Y	Y	/	/	/
Industry-year FE	Y	Y	Y	Y	/	/	/
Province-year FE	Y	Y	Y	Y	Y	Y	Y
City-fixed effects	N	N	N	N	Y	Y	Y
K-P rk LM statistic	94.699	94.755	82.161	88.038	195.4	195.4	195.4
K-P rk Wald F statistic	408.69	408.62	111.46	177.79	709.1	709.1	709.1
Hansen J statistic (p value)	0.6147	0.1239	0.2753	0.2243	0.00892	0.0418	0.395

Notes: This table presents the 2SLS estimated impacts of air connectivity on SO_2 generation (in kilograms) and removal (in kilograms), output, coal consumption of firms, and the industrial composition of cities. The relationship among these variables is defined as SO_2 emission = SO_2 generation - SO_2 removal. Column 3 reports the 2SLS estimated impacts of air connectivity on firm value-added industrial output. Column 4 reports the impact of air connectivity on total coal consumption by the firm. Columns 5 to 7 reports the impact of air connectivity on city industrial composition, specifically in primary, secondary and tertiary industry. The control variables in the regressions presented in columns 1 to 4 are consistent with those in Table 3. Columns 5 to 7 include only city-level control variables from Table 4.3. The first-stage regression results are not reported here to save space; only the statistics of the first-stage regression are presented. The two instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

Since SO_2 is one of the primary pollutants from coal combustion, advancements in production technology may enable firms to achieve the same output while consuming less coal, thereby lowering SO_2 emissions. Enhanced air connectivity may reduce total coal consumption by firms, thereby lowering SO_2 emissions. To test this hypothesis, Column 4 reports the impact of air connectivity on total coal consumption by firms estimated using 2SLS. The results indicate that air connectivity does not significantly affect total coal consumption by firms.

Research indicates that the opening of high-speed rail (HSR) can advance industrial structure (Jiang et al., 2022). Accordingly, improvements in air connectivity and the opening of new airports may also promote urban industrial upgrading. Therefore, at the city level, we investigated the impact of air connectivity on industrial development, using the proportions of the primary, secondary, and tertiary industries within the gross regional product (GRP). The primary industry percentage is defined as the value of the primary industry relative to the gross regional product (GRP). The data were compiled from the Chinese Research Data Services Platform (CNRDS) and the Chinese City Statistics Database (CCSD). As detailed in columns 5 to 7 of table 4, results indicate that during our research period, the development of city air connectivity did not significantly alter the city-level industrial composition.

The impact of air connectivity on new business registration across various industries

To further explore the impact of enhanced air connectivity on city industry development, we examined the influence of air connectivity on the number of new registered firms across various industries, which reflects the dynamic development of city industries and the state of entrepreneurship. We obtained data on the number of newly registered firms in each industry in each city from the Chinese industrial and commercial registration website and used 2SLS to investigate the effect of air connectivity on this metric. The regression model is the same as Equation 4.7, with the independent variable being the $newly\_registered\ number_{ct}$, representing the number of newly registered firms in industry c at year t.

In Figure 4.7, we present the coefficients of air connectivity and their 95% confidence intervals obtained from the regression analysis, excluding other control variables for simplicity. The industry codes alongside their names can be referenced in Table E1. As depicted in Figure 4.7, improved air connectivity of a city significantly increases the number of new registered firms in the accommodation and food service sector (industry code H), the leasing and business services industry (industry code L), the scientific research and technical services industry (industry code M), and the resident services, repairs and other services industry (industry code O). This indicates that air connectivity fosters the development of the service industry in cities, although it does not significantly affect the value of the tertiary industry. The significantly positive impact on the scientific research and technical services industry also suggests that enhanced air connectivity promotes city scientific research development and fosters innovation. On the other hand, the manufacturing industry, denoted by code C, exhibits a non-significant deviation from zero, indicating that air connectivity does not have a significant impact on the registration of new manufacturing firms. All this analysis shows that improved air connectivity leads to the development of the service industry and the concentration of high-tech firms, thereby driving technological advancements.

To further identify the mechanism, we use the number of new registration firms in the scientific research and technical services industry as a mediating variable to test its impact on firm SO2 emissions. The regression model is shown in equation 4.8.

$$NewFirmM_{kpt} = \alpha_0 + \alpha_1 \ln \widehat{Airconnectivity}_{kt} + Z'_{kt}\varphi + \tau_k + \omega_{pt} + \varepsilon_{rkpt} \tag{4.8}$$

$$\ln SO_{2_{ijkpt}} = \beta_0 + \beta_1\, NewFirmM_{kpt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \tag{4.9}$$

$$\ln SO_{2_{ijkpt}} = \gamma_0 + \gamma_1\, NewFirmM_{kpt} + \gamma_2 \ln \widehat{Airconnectivity}_{kt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \tag{4.10}$$

where $NewFirmM_{kpt}$ refers to the number of newly registered firms in industry M, the scientific research and technical services industry, in city k, province p, in year t. The regression results are summarized in Table 4.5. Column 1 reports the impact of air connectivity on the number of newly registered firms in industry M, indicating that a 1% increase in air connectivity will significantly increase new business registrations in this industry by 0.38. Given that the average air connectivity increase ratio for the 143 airport cities in China in 2013 was 23%, this translates to an average promotion of 9 new business registrations in industry M for each city. Columns 2 and 3 report the impacts of new business registration on firm SO_2 generation and removal, suggesting that growth in the scientific research and technical services industry promotes technological advancements in the production process rather than in the emission control process. Specifically, for each additional new firm registered, SO_2 generation during the production process decreases by 0.007%. Given the results from Column 5, we can interpret that the development of industry M is part of the mediating effect through which air connectivity facilitates emission reductions. This highlights the significant role that new firm registrations in the scientific research and technical services sector play in enhancing production efficiency and contributing to overall emission reductions, reinforcing the idea that improved air connectivity not only fosters business growth but also supports environmental goals.

Table 4.5 The mediating effect of the city scientific research and technical services industry development

Dependent variables	(1) New firm in industry M	(2) ln SO_2 removal	(3) ln SO_2 generation	(4) ln SO_2 generation	(5) ln SO_2
New firm in the scientific research and technical services industry		-0.000	-0.00007*	-0.00007*	-0.00004
		(0.000)	(0.000)	(0.000)	(0.000)
ln Air Connectivity	38.1***			-0.093**	-0.101***
	(11.4)			(0.038)	(0.036)
Control Variables	City-level	Y	Y	Y	Y
Observations	2,430	172,233	172,086	172,086	255,103
Firm fixed effects	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y
City fixed effects	Y	N	N	N	N
K-P rk LM statistic	153.7	.	.	93.90	136.0
K-P rk Wald F statistic	700.7	.	.	410.1	501.8
Hansen J statistic (p value)	0	.	.	0.408	0.0434

Note: This table presents mediating model results using the number of newly registered firms in the scientific research and technical services industry. Column 1 includes city-level control variables from Table 3. The control variables in columns 2 to 5 are consistent with those in Table 4.3. The instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

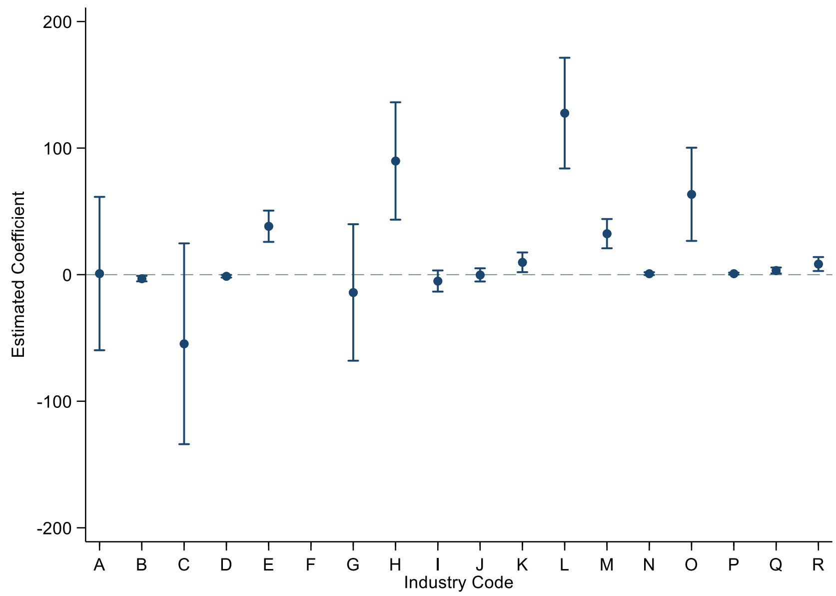


Fig. 4.7: The impact of air connectivity on the number of newly registered firms across various industries (IV)

Notes: This table presents the 2SLS estimated impacts of air connectivity on the number of new registered firms in each industry, along with the corresponding 95% confidence intervals. The control variables and fixed effects mirror those in Table 4.3, with the coefficients of control variables excluded. The industry codes alongside their corresponding names are in Table E1. The instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

The impact of air connectivity on firm patent applications

In this subsection, we collect annual patent application data of manufacturing firms to capture the knowledge diffusion effect. The total number of patent applications can be segmented into invention patents, design patents, and utility patents. The mediating model is shown below.

$$\ln \text{Patent}_{ijkpt} = \alpha_0 + \alpha_1 \ln \widehat{Airconnectivity}_{kt} + X_{it}'\delta + Z_{kt}'\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \quad (4.11)$$

$$\ln SO_{2_{ijkpt}} = \theta_0 + \theta_1 \ln \widehat{Airconnectivity}_{kt} + \theta_2 \text{Patent}_{ijkpt} + X_{it}'\delta + Z_{kt}'\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \quad (4.12)$$

The above regression models can identify the mechanisms through which air connectivity influences SO_2 emissions, differentiating between emissions generation and emissions removal. The results are summarized in Table 4.6. Columns 1 to 4 present the impact of air connectivity on firm patent applications, indicating that a well-connected aviation network boosts the application of invention and utility patents among manufacturing firms. Similar results are found in other research. Bahar et al. (2023) concluded that an increase in nonstop flights between two locations leads to higher citation rates and greater production of collaborative patents, thereby fostering corporate innovation. Increased innovation in utility patents enhances "end-of-pipe" emission control efficiency and improves SO_2 removal. However, this rise in utility patent innovation does not lead to increased production efficiency or a reduction in SO_2 generation. Regarding invention patents, the increase in invention patent applications does not significantly impact emissions generation or control; instead, they may influence manufacturing firm performance in other ways.

Table 4.6 The mediating effect of firm patent applications industry development

Dependent variables	(1) Total patent	(2) Invention patent	(3) Design patent	(4) Utility patent	(5) ln SO_2 generation	(6) ln SO2 removal	(7) ln SO2 removal	(8) ln SO_2
ln Air Connectivity	0.192	0.171*	-0.095	0.117*			0.278**	-0.075**
	(0.175)	(0.090)	(0.073)	(0.067)			(0.129)	(0.038)
Utility patent					0.001	0.004**	0.004**	0.0004
					(0.002)	(0.002)	(0.002)	(0.002)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y
Observations	255,103	255,103	255,103	255,103	172,068	172,068	172,068	255,103
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Province-year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
IVs	IV2	IV2	IV2	IV2	/	/	IV2	IV2
K-P rk LM statistic	136.1	136.1	136.1	136.1	.	.	93.09	136.12
K-P rk Wald F statistic	553.4	553.4	553.4	553.4	.	.	397.3	553.40
Hansen J statistic (p value)	.	.	.	.	.	.	.	.

Notes: This table presents the estimated impacts of air connectivity on firms' patent applications and emissions. Columns 1 to 4 show the effects of city air connectivity on the number of patent applications at the firm level. Columns 5 and 6 show the effect of the number of utility patent applications on firm SO_2 generation and removal. Columns 7 and 8 demonstrate the joint effect of city-level air connectivity and firm-level utility patent applications on SO_2 emissions from firms. The control variables mirror those in Table 4.3. The results of the first-stage regression are not reported here to save space; only the statistics from the first-stage regression are included. The two instruments are defined in Equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The impact of air connectivity on firm green production efficiency

The knowledge diffusion facilitated by the aviation network may not only promote firms' research and development but also enhance their green production efficiency. Following Shao et al. (2021), we construct a firm green production efficiency index that ranges between 0 and 1, with higher values indicating greater green production efficiency. The primary approach is based on the Slacks-Based Measure of Efficiency with Directional Distance Function (SBM-DDF) and the Global Malmquist-Luenberger (GML) index for measurement. First, each firm is treated as a decision-making unit, and we construct the global production possibility set and the global SBM-DDF for each firm. Based on this, we build the GML productivity index, and finally derive the firm's overall green efficiency index through the decomposition of the GML productivity index. The regression models are shown below.

$$\ln \text{Green\_effi}_{ijkpt} = \alpha_0 + \alpha_1 \ln \widehat{Airconnectivity}_{kt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \tag{4.11}$$

$$\ln SO_{2_{ijkpt}} = \rho_0 + \rho_1 \ln \widehat{Airconnectivity}_{kt} + \rho_2 \ln \text{Green\_effi}_{ijkpt} + X'_{it}\delta + Z'_{kt}\varphi + \gamma_i + \eta_{jt} + \omega_{pt} + \varepsilon_{ijkpt} \tag{4.12}$$

The regression results are summarized in Table 4.7. Column 1 reports the impact of air connectivity on firm green production efficiency, indicating that improved air connectivity significantly increases firm green production efficiency by 0.0002% for every 1% increase in connectivity. We collected data on the number of first-class and business-class passengers arriving in the city each year as a measure of business interactions facilitated by air travel, serving as a proxy for knowledge diffusion. Column 2 reports the impact of business travelers on firm green production efficiency. The results are similar to those in Column 1, showing that for every 1% increase in business travelers, firm green production efficiency improves by 0.0001%. Columns 3 and 4 indicate the significant impact of green production efficiency on both SO_2 generation and SO_2 removal. Columns 5 and 6 present results that include both air connectivity and green production efficiency. The significant coefficient of green production efficiency and the insignificant coefficient of air connectivity suggest that air connectivity contributes to emission reductions primarily by enhancing firms' green production efficiency.

Table 4.7 The mediating effect firm green production efficiency

Dependent variable	(1) ln green production efficiency	(2) ln green production efficiency	(3) ln SO2 generation	(4) ln SO2 removal	(5) ln SO2 generation	(6) ln SO2 removal	(7) ln SO2
ln green production efficiency			-6.400*** (0.866)	5.894** (2.563)	-6.400*** (0.866)	5.933** (2.570)	-9.901*** (1.439)
ln Air Connectivity	0.0002* (0.00016)				0.000 (0.033)	-0.121 (0.187)	0.010 (0.029)
ln business passenger		0.0001** (0.00005)					
Control Variables	Y	Y	Y	Y	Y	Y	Y
Observations	120,464	120,464	59,757	59,755	59,757	59,755	120,464
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y	Y
K-P rk LM statistic	101.8	85.66	.	.	74.151	74.151	101.78
K-P rk Wald F statistic	228.7	125.9	.	.	186.94	186.94	228.65
Hansen J statistic (p value)	0.0285	0.205	.	.	0.01889	0.1239	2.436e-04

Notes: This table presents mediating model results using firm green production efficiency. The instruments are defined in equations 4.3 and 4.4. The control variables mirror those in Table 4.3. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

The above analysis can be summarized from both production and emission control perspectives. Knowledge diffusion facilitated by a more accessible aviation network, along with the frequent interactions of business travelers, has promoted the development of the service sector in destination cities. This has led to a significant increase in the number of new firms in research-related industries, a notable rise in patent applications at the firm level, and an enhancement in firms' green production efficiency. The growth in the scientific research and technical services industry can facilitate emission reductions from the production process by improving production efficiency and reducing emissions generation without influencing output. The increased patent applications contribute to emission reductions from the emission control process by enhancing emission removal. Furthermore, the rise in green production efficiency will lead to reductions in emissions from both production and emission control processes. The impact mechanism of air connectivity on firm SO_2 emissions is illustrated in Figure 4.8.

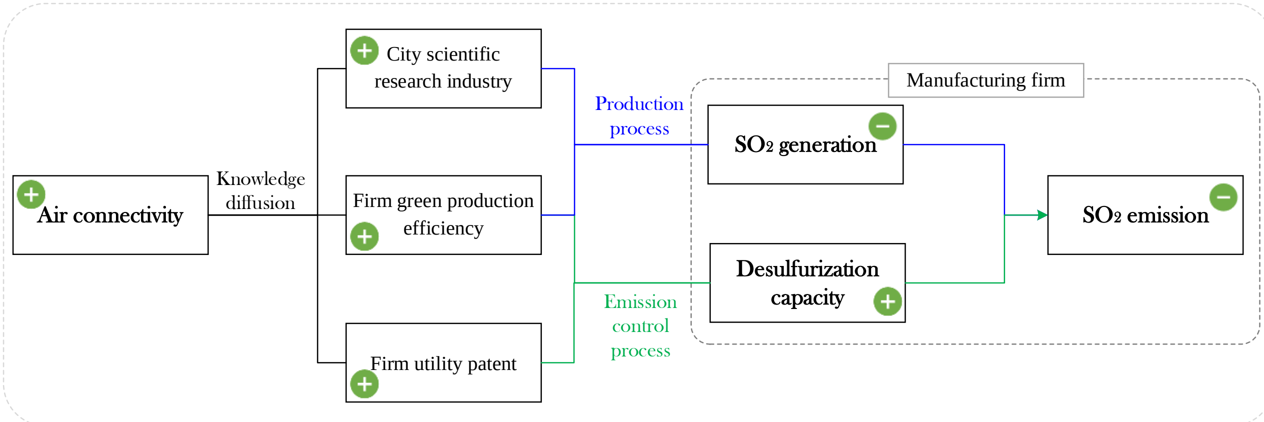


Fig. 4.8: The impact mechanism of air connectivity on firm SO_2 emissions

4.6.3 Robustness checks

Test on other pollutions. We examine whether city air connectivity impacts other emissions of manufacturing firms. As illustrated in Table 4.8, we present the 2SLS estimated results of air connectivity on firm waste gas emissions. The results align with the regression results for SO_2, demonstrating that improved air connectivity significantly and negatively influences atmospheric pollutant emissions of firms. We also examined the effect of air connectivity on SO_2 emissions per unit of output to assess its impact on SO_2 emission intensity. The results presented in Table 4.8, column 2, demonstrate that city air connectivity significantly reduces the SO_2 emission intensity of firms, further confirming our hypothesis regarding the emission reduction effects of city air connectivity.

Alternative samples. To further reduce potential endogeneity, we excluded 32 provincial capitals and sub-provincial cities from the regression analysis. These cities have well-connected aviation networks and are more environmentally conscious. The results in Table 4.3 may be affected by the distinct characteristics and dynamics of these larger cities. As shown in Table 4.8, column 3, even after excluding these major cities, the regression results indicate that air connectivity still significantly reduces firms' SO_2 emissions. We observe that for every 1% increase in air connectivity, there is a notable 0.1% decrease in SO_2 emissions from firms, which is the same as the coefficient in Table 4.3 (-0.100), suggesting that there is no significant difference among major cities and other cities.

All these robustness checks yield results consistent with our baseline findings, further validating the reliability of our conclusions.

Table 4.8 The impact of city air connectivity on firm emissions (robustness checks)

	(1)	(2)	(3)
	Other firm emissions	Firm SO_2 emission intensity	Firm SO_2 excluding major cities
Dependent variables	ln gas	ln SO_2 intensity	ln SO_2
ln Air Connectivity	-0.065*	-0.087**	-0.098***
	(0.037)	(0.035)	(0.036)
Control Variables	Y	Y	Y
Observations	149,738	254,875	176,416
Firm fixed effects	Y	Y	Y
Industry-year fixed effects	Y	Y	Y
Province-year fixed effects	YES	YES	YES
City fixed effects	/	/	/
K-P rk LM statistic	88.71	136.6	127.3
K-P rk Wald F statistic	176.6	499.7	506.7
Hansen J statistic (p value)	0.650	0.0197	0.1354

Notes: This table presents the 2SLS estimated impacts of air connectivity on various emissions. Columns 1 shows the effects of city air connectivity on waste gas emissions. Column 2 shows the effect on firm SO_2 emission intensity as measured by SO2 emissions per unit of output. Column 3 shows the effect on SO_2 emissions of firms after excluding 32 major cities. The control variables mirror those in Table 4.3. The first-stage regression results are not reported here to save space; only the statistics of the first-stage regression are presented. The two instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.6.4 Heterogeneity analysis

In this section, we investigate the heterogeneous effects of city air connectivity on firm SO_2 emissions, using the two instruments defined in the previous section. First, we examine whether the estimated impact of connectivity on firm SO_2 emissions varies by regions, as there are significant disparities in development across different regions of China; the eastern region is more economically developed, while the western region is less developed. We divide the full sample into three subsamples (western, central, and eastern) and re-estimate equations (5) and (6). Holding all else constant, cities in the eastern region experienced a much higher reduction in emissions, as shown in Table 4.9, columns 1 to 3.

In the second investigation, we assess whether the impact of city air connectivity on firm SO_2 emissions differs based on the number of major cities the origin city is connected to. We do this because provincial capitals or municipalities are usually the most economically developed cities in a province or country, and they have distinct advantages in knowledge creation. Due to their political significancande, they receive more resources, and many high-tech firms are based in these cities. If a city is connected to major cities through more frequent direct flights, it has the opportunity for easier knowledge diffusion, facilitating technological advancement. We split the full sample into two subsamples based on the average number of major cities to which the origin city is connected during the sample period, using k-means cluster analysis (connected to more major cities, connected to fewer major cities). Similarly, we also split the sample according to the city's international flight ratio ($International\ flight\ ratio_{kt} = f\_International\ flight_{kt}/f_{kt}$), and the international connectivity of the destinations ($Destination\ international\ connectivity_{kt} = \sum_{d=1}^{N_{kt}} \left(\frac{f\_international_{dt}}{f_{dt}}\right) f_{kdt}^{\frac{\sigma-1}{\sigma}}$). The regression results are displayed in Figure 4.9. In the group connected to more major cities, for every 1% increase in city air connectivity, the SO_2 emissions of firms significantly decrease by 2.09%. This coefficient is significantly larger than the 0.1% impact found in the full sample regression (Table 4.3, Column 6), indicating that air connectivity has larger negative impacts on firm SO_2 emissions if the city is connected to more major cities. This indirectly confirms our hypothesis regarding knowledge diffusion and technological advancement mechanisms: when a city establishes air connections with more major cities that are leaders in economic development and scientific innovation, it can more easily access knowledge and technical expertise from these cities. This enhanced access to knowledge can improve firms' production efficiency and pollution control capabilities, leading to reduced emissions.

Regarding the heterogeneity impact of international flights, a city connected to more international destinations also benefits from the diffusion of knowledge. The coefficient for this connection is larger than that for cities with fewer international destinations (-1.235 vs. -0.090), indicating a significant influx of knowledge and innovation from abroad. However, this impact is still less than the influence experienced by cities connected to more domestic major cities (-2.089). This suggests that while international connections provide valuable opportunities for knowledge exchange, domestic major cities offer a more substantial benefit in terms of innovation transfer. The stronger impact of domestic connections can be attributed to the proximity of cultural, economic, and technological practices among domestic firms, which often leads to more effective collaboration and faster adaptation of innovations. Domestic networks facilitate face-to-face interactions, enhance trust among local firms, and create a shared understanding of market dynamics, all of which are crucial for effective knowledge diffusion. In contrast, while international connections broaden the scope of knowledge access, they may also introduce complexities related to cultural differences and varying market conditions, making it more challenging for firms to leverage these innovations effectively. Thus, for cities, the benefits derived from connections to domestic major cities appear to outweigh those from international destinations in fostering innovation and technological advancement.

However, when examining the heterogeneous effect of being connected to more international destinations in relation to domestic connections, it becomes clear that a city linked to domestic cities with more international flights does not experience a significant impact. This suggests that knowledge diffusion, whether it originates from domestic or international connections, primarily occurs through direct flights rather than transfer flights. This finding highlights the importance of direct air connectivity in maximizing the benefits of knowledge diffusion, whether from domestic or international sources. This is also consistent with the findings from Bahar et al. (2023), which indicate that a 10% increase in nonstop flights between two locations results in a 3.4% increase in citations and a 1.4% rise in the production of collaborative patents between those locations.

Table 4.9 The impact of city air connectivity on firm SO_2 emissions (heterogeneity analysis)

	(1)	(2)	(3)
	Firm SO_2 emissions across different regions		
Dependent variables	ln SO_2_Eastern	ln SO_2_Central	ln SO_2_Western
ln Air Connectivity	-0.140***	-0.040	0.035
	(0.051)	(0.046)	(0.056)
Control variables	YES	YES	YES
Observations	157,998	65,221	31,879
Firm FE	YES	YES	YES
Industry-year FE	YES	YES	YES
Province-year FE	YES	YES	YES
K-P rk LM statistic	63.18	82.86	75.50
K-P rk Wald F statistic	236.9	245.2	145.1
Hansen J statistic (p value)	0.0975	0.197	0.722

Notes: This table presents the 2SLS estimated impacts of city air connectivity on SO_2 emissions of firms across different regions. The control variables mirror those in Table 4.3. The first-stage regression results are not reported here to save space; only the statistics of the first-stage regression are presented. The two instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

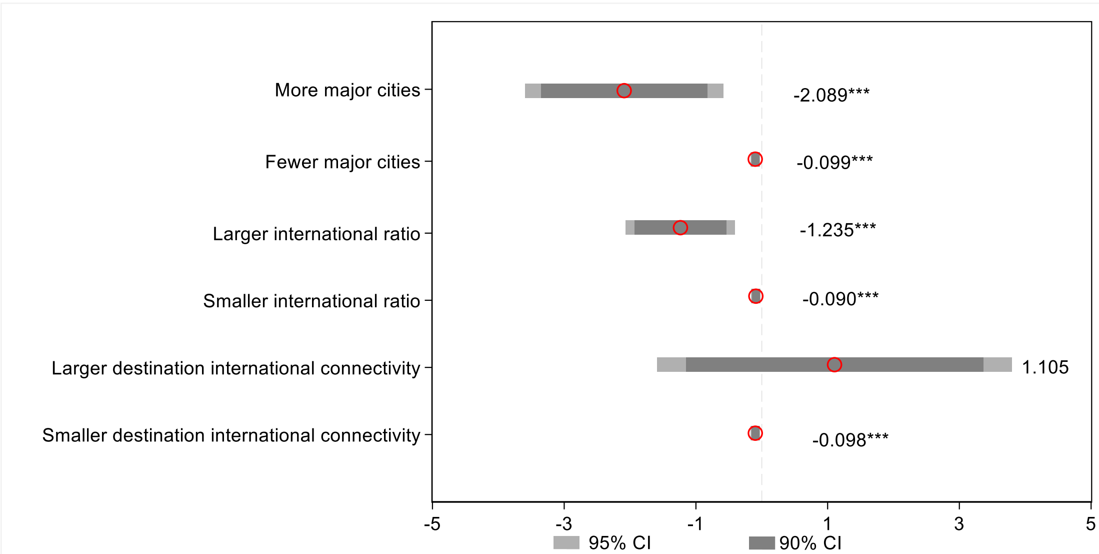


Fig. 4.9: The impact of city air connectivity on firm SO_2 emissions (heterogeneity analysis)
Notes: This figure shows the heterogeneous effect of city air connectivity on firm SO2 emissions using the IVs. Each estimate is obtained by estimating equations 4.5 and 4.6 and using subsamples. The subsamples are generated as follows: (1) considering the number of major cities the origin city is connected to; (2) the international flight ratio of the origin city; (3) the international connectivity of destinations of the origin city. The control variables mirror those in Table 4.3. The supporting regression results of the figure are presented in Appendix Table E2. (4) CI: confidence intervals.

4.6.5 Deaths prevented and years of life saved by improved air connectivity

The level of air pollution in China continues to be severe. The annual average SO_2 concentration in 113 major Chinese cities in 2019 was 42 μg/m^3, which was higher than the World Health Organization's (WHO) suggested air quality guideline level of 40 μg/m^3. According to the WHO report, in 2019, ambient (outdoor) air pollution was estimated to result in 4.2 million premature deaths globally annually[35]. The Chinese government has adopted more stringent measures to mitigate air pollution and prevent such human fatalities. Based on the previous analysis, we examine how air connection improvements contributed to the decrease in ambient SO_2 levels from 2005 to 2013, as well as the prevented human deaths and years of life lost.

Although we have shown that enhanced city air connectivity will reduce enterprise SO_2 emissions, the enhanced aviation activities also contribute to emissions and impact

[35] See the related report at https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

city SO_2 concentrations and air quality. To fully quantify the impact of city air connectivity on human health, we conducted an empirical model first to evaluate the overall effects of enhanced city air connectivity on city SO_2 concentration levels and then connect the estimation with human mortality. The second-stage regression model of the impact of city air connectivity on city SO_2 concentration levels is outlined in equation 8, with the instruments defined in equations 3 and 4. Data on city SO_2 concentrations was sourced from NASA[36]. The regression results are detailed in Table 10. As stated in Column 3, a 1% increase in city air connectivity is associated with a reduction of 0.170 $\mu g/m^3$ in city SO_2 concentration. It is interesting to observe in Table 10 that other transport infrastructure, such as HSR and road density, is significantly negatively related to city-level SO_2 concentration. Even after controlling the ratios of tertiary and secondary industries, industrial output, and using HSR frequency to capture its effects, the impact remains negative. Furthermore, our earlier regression results indicate that, when controlling for city civil aviation development during the 2005-2013 study period, the opening of HSR did not have a significant impact on industrial SO_2 emissions at the firm level (as shown in Table 4.3, Column 6). However, it does appear to increase city-level SO_2 concentration. One possible explanation for this phenomenon is that China's HSR development was still in its early stages from 2005 to 2013, with the first HSR line opening in 2008 and most of China's network being built after 2012. Although many scholars have explored the impact of HSR on city air quality, most studies have focused on CO concentration, PM2.5 concentration, and AQI indexes without adequately controlling for the influence of civil aviation development. This makes direct comparisons difficult. Future studies could further investigate the impact of HSR on firm emissions using recent years' data, if emission data is available. Another reason could be that our data is based on yearly averages, which is too coarse to fully capture variations in air quality.

In order to quantify the air quality enhancement led by air connectivity improvements in each city from 2005 to 2013, we calculated the proportional increase in air connectivity for each city and multiplied it by the coefficient (-0.170) from Table 10 Column 3. This

[36] Data source:
MERRA-2 tavgM_2d_aer_Nx: 2d,Monthly mean,Time-averaged,Single-Level,Assimilation,Aerosol Diagnostics V5.12.4 data. https://disc.gsfc.nasa.gov/datasets?keywords=M2TMNXAER_5.12.4&page=1

yielded the reduction in city SO_2 concentration achieved by technological advancements in enterprises and related pollution sources due to improved air connectivity. After obtaining the changes in SO_2 concentrations for each city, for simplicity, by averaging across cities, we derived a national reduction in SO_2 concentration of approximately 0.653 $\mu g/m^3$. By combining our results with relevant literature on pollution and health, such as Wang et al. (2018c), who investigated the impact of SO_2 concentrations on mortality rates in 272 Chinese cities and found that for every 10 $\mu g/m^3$ increase in two-day average SO_2 concentrations, there was a 0.59% rise in mortality from all non-accidental causes. Similar estimations were also discovered in other studies in China and Europe, as summarized in Table 4.11. Therefore, the reduction of 0.653 $\mu g/m^3$ in SO_2 concentration was linked with a 0.03853% decrease in total mortality (0.59% / 10 * 0.653). The mortality rate in 2005 was 550.75per 100,000 individuals, and the population of China in 2005 was 130628 million people[37]. Therefore, the estimated number of prevented deaths due to improved air quality resulting from enhanced air connectivity was calculated to be 2772 (0.03853% * 550.75* 13062.8).

However, the number of deaths only accounts for the frequency of deaths and does not reflect the ages at which deaths occur. A decrease in SO_2 concentration primarily helps reduce mortality rates from cardiovascular diseases and respiratory diseases, which together constitute almost 60% of total non-accidental deaths. According to Wang et al. (2018c), for every 10 $\mu g/m^3$ decrease in SO_2 concentrations, there was a 0.70% reduction in deaths from total cardiovascular diseases and a 0.55% decrease from total respiratory diseases. Since the majority of deaths from these diseases occur in the elderly population, reducing SO_2 concentrations would be beneficial for constructing an elderly-friendly society. We calculated the prevented deaths from total cardiovascular diseases and total respiratory diseases, which amount to 1375 and 453, respectively. Other deaths not attributed to these causes were categorized as others, totaling 944. By integrating data on the age distribution at the time of death with the WHO's life table, we computed the years of life lost (YLL), a variable capturing premature mortality by considering both the frequency of deaths and the age at which they occur. The reduced YLL from 2005 to 2013

[37] The non-accidental mortality data is sourced from China's Disease Surveillance Points System (DSPS). The population data for China is sourced from census data.

amounted to 38473 years. The calculation flow for the prevented number of deaths and reduced YLL is shown in Figure 4.10.

These health benefit calculations are approximations. We utilized the average SO_2 concentration of cities to evaluate the country-level decrease in concentration. When estimating the total prevented deaths at country level due to improvements in air quality, we assumed that the established relationship between pollution and mortality, derived from the analysis of 272 Chinese cities (Wang et al., 2018c), is applicable to our study. Nevertheless, our calculations suggest that the health benefits resulting from prevented deaths due to the enhancement of air quality driven by air connectivity are substantial. However, it is important to note that our estimation only considers the 118 airport cities in 2005. We did not account for the health benefits associated with airport expansion resulting from the rapid development of civil aviation in China after 2005. By 2013, China had 160 airport cities. Therefore, our estimates overlook the health effects of civil aviation development in China from 2005 to 2013.

$$\ln SO_2concentration_{kpt} = \theta_0 + \theta_1 \ln \widehat{Airconnectivity}_{kt} + Z'_{kt}\varphi + \rho_k + \omega_{pt} + \varepsilon_{ijkpt} \quad (13)$$

Table 4.10 The impact of city air connectivity on city SO_2 concentration

Dependent variables	(1) City SO_2 concentration	(2) City SO_2 concentration	(3) City SO_2 concentration
ln Air Connectivity	-0.055	0.152	-0.170*
	(0.089)	(0.119)	(0.090)
ln GDP	1.728**	1.678**	1.756**
	(0.712)	(0.710)	(0.714)
ln GDP per capita	-1.787**	-1.735**	-1.816**
	(0.731)	(0.730)	(0.732)
Road density	1.056***	1.139***	1.009***
	(0.354)	(0.344)	(0.361)
HSR	0.566***	0.577***	0.560***
	(0.114)	(0.114)	(0.114)
ln Education	0.103	0.124	0.092
	(0.134)	(0.134)	(0.135)
Environmental regulation	-25.378	-24.567	-25.831
	(17.312)	(17.308)	(17.366)
Observations	2,289	2,289	2,289
IVs	IV1 and IV2	IV1	IV2
City FE	Y	Y	Y

Province-year FE	Y	Y	Y
K-P rk LM statistic	196.4	120.6	195.3
K-P rk Wald F statistic	709.5	443.8	913.2
Hansen J statistic (p value)	0.0004	.	.

Notes: This table presents the 2SLS estimated impacts of city air connectivity on city SO_2 concentration using the different instrument variables. Column 1 reports the results obtained using both instruments. Column 2 used the first instrument, and column 3 used the second instrument. The first-stage regression results are not reported here to save space; only the statistics of the first-stage regression are presented. The two instruments are defined in equations 4.3 and 4.4. Robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.11 The estimations of city SO_2 concentration on mortality

Literature	Study area	Conclusion A 10-$\mu g/m^3$ increase in SO_2 is associated with
Wang et al., 2018c	272 Chinese cities, 2013-2015	A 0.59% increase in mortality from total nonaccidental causes
Sunyer, Atkinson et al., 2003	7 European cities, 1988-1997	A 1.3% increase in the daily number of child admissions for asthma
Chen et al., 2012	17 Chinese cities, 2001-2008	A 0.75% increase in total mortality
Kan et al., 2010	4 Asia cities, 1999–2004	A 1.00% increase in total mortality
O'brien et al., 2023	399 cities within 23 countries, 1980 -2018	A relative risk of mortality of 1.0045
Ballester et al., 2002	13 Spanish cities, 1990–1996	A 0.5% increase in daily deaths

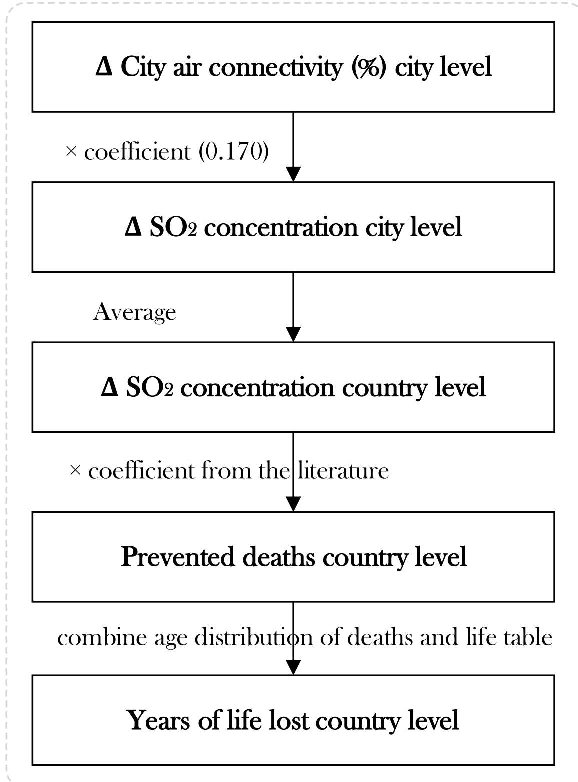


Fig. 4.10: Flowchart for calculating prevented deaths due to improved air connectivity

4.7 Summary

The primary purpose of this study is to investigate the effect of improved air connectivity among cities on the SO_2 emissions of manufacturing firms from the perspective of innovation and technological advancement. We also investigate the underlying mechanism and quantify the health impacts of emission reduction due to enhanced air connectivity. The results from the empirical model show that improved air connectivity significantly reduces manufacturing firms' SO_2 emissions by enhancing their desulfurization capabilities and reducing SO_2 generated during production. These impacts are larger when the city is connected to more major domestic cities. We also quantify the health impacts of improved air quality. This study provides important empirical evidence that air connectivity promotes not only a city's economic development but also its environmental sustainability as well as human health. This study also provides evidence that knowledge diffusion driven by air connectivity is an effective channel for firms to make technological advancements and reduce their pollutant emissions. The health impact of such emission reduction is significant, potentially saving thousands of lives.

This study has several limitations that limit the generalizability of its results. The most obvious limitation is that the sample is drawn only from China, whose situation may differ from that in developed countries. Another limitation is the research period, as the latest data are from 2013. However, given the data availability and our research question, we believe that our findings are robust. Future research could measure the health impact of improved air quality resulting from enhanced air connectivity by utilizing more specific city-level data.

CHAPTER 5.

CONCLUSIONS AND FUTURE WORK

In the context of the rapid development of the global aviation network, this thesis explores the aviation system's response to the COVID-19 pandemic and the benefits of a well-connected aviation network, focusing on service trade and emissions. We aim to address the following research questions: (1) How do airlines respond to the COVID-19 pandemic? Does competition among airlines become more intense or less intense? (2) How do multi-airport systems respond to the COVID-19 pandemic? (3) How does country-level air connectivity affect bilateral service trade? (4) Do open skies agreements promote service trade? (5) How does city-level air connectivity impact emissions from manufacturing firms? Through a comprehensive empirical analysis, we present the main conclusions, limitations, and suggestions for future research related to each research question as follows.

In study 1, we find that during the pandemic, Spring Airlines has actively expanded its network to all types of routes, especially the dense routes connected to major airports. FSCs also adjusted their route entry strategy by entering more thin routes connected to secondary cities. The pandemic has broken the pre-pandemic equilibrium of network differentiation between FSCs and Spring Airlines. Overall, we observe more frequent market contact and increasing head-to-head competition between FSCs and Spring Airlines as the pandemic is under control. This study supplements the findings of previous literature with new insights and contributions. This is the first empirical study to disentangle the attenuating and persistent effects of the pandemic on airlines' route choice. Second, we measured the change in market contact between FSCs and Spring Airlines in the Chinese domestic market. Although the study is carried out in the context of the Chinese market, the implications may provide different perspectives for analyzing other major and emerging airline markets of similar size and legacy regulations.

Despite the large sample size and robustness checks, study 1 is still subject to some limitations, while opening avenues for future studies. First, our study focuses on the overall competition pattern between FSCs and Spring Airlines, but does not look into each specific airline's competition decisions. As the Chinese domestic market is dominated by the Big Three airlines, their mutual competition interactions have likely been affected by the pandemic and deserve a closer examination in future studies. Second, the ticket price and passenger traffic data were subject to significant measurement errors during the pandemic. Thus, we chose not to estimate the airline price and demand functions. If more accurate and reliable data can be obtained, relevant studies can be conducted to offer additional results from different perspectives. Third, since September 2020, CAAC has lessened the entry restriction of feeder routes connecting with major hub airports in China, namely Beijing, Shanghai, and Guangzhou. We have tried to explicitly disentangle this specific CAAC deregulation policy from the estimated overall pandemic impact. However, it proves hard to empirically identify such policy effects with our dataset. Therefore, the route choice effect this study estimated is the combined impact of the pandemic and CAAC deregulation policy. Fourth, although we attempted to minimize potential biases resulting from omitted variables by including control variables, fixed effects, and using IV methods, this study may still be subject to potential estimation bias. For example, we have not considered the possible heterogeneous impact of the pandemic on different FSCs. That said, our estimation mainly reflects the average impact. Additionally, omitted variables at the airline level, such as the airline network scale, the share of domestic routes, and international routes before the pandemic, could also affect our estimation results. Other variables, such as weather conditions over time, can also potentially impact airlines' route entry decisions. However, due to limitations in data availability, this study is unable to control for all of these factors. A more in-depth analysis of the heterogeneous pandemic impact on airlines could be explored in future studies when the data is available and leverage on more sophisticated econometric models. Finally, we only chose data up until the end of 2022. Our findings may not be generalized in a much longer period post-pandemic, especially when the Chinese government has already fully lifted its border control. When international flight services and networks resume, the major Chinese airlines will resume their international services and thus re-adjust their domestic market competition strategy. We hope our study can lead to more advanced empirical approaches and research designs to overcome such limitations. All these areas are meaningful extensions but are beyond the scope of the current study.

In study 2, our statistics suggest heterogeneous impacts of the pandemic on MASs in different regions when comparing market outcomes between Q3 2019 (before the pandemic) and Q3 2022 (during the pandemic). For MASs in the US and Europe, the distribution of traffic and degree centrality among airports remained largely unchanged. Both the domestic and international airline markets in these MASs have returned to pre-pandemic levels at similar paces. Until the end of 2022, intra-MAS airport competition and airline airport dominance and concentration (including between FSCs and LCCs) have also been similar to pre-pandemic levels at major European and US MASs. These results suggest the stability of MAS structures in the US and Europe after their airline markets recovered from the unprecedented shock of the pandemic. In contrast, Asia-Pacific MASs experienced significant changes during the pandemic, mainly due to very restrictive bans on international travel. Since large-sized airlines could not serve international markets, they had to redeploy their capacity into domestic markets, leading to significant changes in the MAS structure. First, airport traffic could be more balanced within the MAS, and intra-MAS airport competition became much fiercer as airports focused on operations in similar domestic destinations. On the other hand, smaller airlines dropped quite a few markets, leading to higher airline concentration levels. The net effect (i.e., whether competition in an MAS increased and decreased) remains unclear. It is also noted that LCCs in Asia-Pacific seemed more likely to have a main base in a single airport in one MAS, either due to the incentive of achieving economies of scale or they were pushed out from other airports due to stronger competitive responses from FSCs who were forced to allocate more capacity to domestic markets.

In general, study 2 identified heterogenous development and recovery patterns among MASs in different regions. Although some possible explanations are proposed, more in-depth analysis is required to go beyond simple statistics. Our study also raised some questions unanswered. For example, government interventions in the European and North American markets, where markets largely returned to pre-pandemic conditions, are probably not necessary. Yet it is not clear whether any government intervention should be considered to address the heterogenous impacts caused by the pandemic, especially for "distortions" caused by previous regulations (e.g., bans on international services).

Extension studies based on updated data can be helpful in addressing those important questions.

In study 3, we examine how air connectivity affects bilateral service trade flow. We chose to use the number of direct flight routes between the country pairs and the average passenger number per route (passenger density) as our measure of air connectivity for this research. Our service trade data includes ‘commercial’ services, ‘transport’ services, and ‘travel’ services. Using Chinese data, a reduced-form gravity-type model is estimated. We used the IV approach in order to deal with the potential endogeneity between bilateral air connectivity and bilateral service trades. Our findings suggest that an increased number of direct routes can significantly promote bilateral service trade export and import, while the average passenger number per route has a marginal effect. Furthermore, an improvement in bilateral air connectivity stimulates China’s total service imports more than exports (especially for transport and travel services), thus expanding the overall service trade deficit for China. Also, an increase in the air connectivity can facilitate ‘commercial’ service export while contributing to the surplus in China’s commercial service trade sector, which accounts for more than 50% of China’s total service trades. To promote its bilateral service trade, China should expand the number of direct routes with its trading partner countries instead of increasing flight frequencies on the existing routes. In other words, the priority should be given to relaxing restrictions on the destinations with direct flights instead of lifting the restrictions on the route-level flight frequencies.

Results in study 3 are derived from real-world data and are also linked with the previous research. However, this study has important limitations. First, our data is only available for the period before the COVID-19 pandemic. The current international connectivity has been significantly restricted due to the pandemic, especially for China, which is implementing the “zero-case” policy. As a result, the effect of air connectivity on service trade may be altered by changing travel behaviors and substituting face-to-face meetings with virtual online meetings. Thus, future studies should be conducted to investigate the COVID-19 impact when the data becomes available. In addition, our gravity-type model is a reduced-form approach, which measures only the net causal effect of air connectivity on bilateral service trade flow. That is, the detailed mechanisms via which service trades are stimulated are not directly addressed in this study since such a study would require the use of a more sophisticated approach by both academics and policymakers. Lastly, on purpose, we chose to use rather simple air connectivity measures because of the enormous data needed for constructing air connectivity between China and each of 45 service trade partner countries for each year of 2005-2018. Unlike other studies focusing on connectivity measurement for specific nodes (i.e., airport or city) in a network, it would be difficult for us to use a more sophisticated connectivity index for each country-pair and each year of our time series. Thus, we chose to use the number of direct routes and average passenger density per route as our air connectivity measures. Another limitation of this study is the restricted coverage of our dataset, which includes only 45 Chinese service trading partners. Such data limitation is because the service trade data is voluntarily reported by the countries' governments, such that the records with some trading partners could be hidden for data quality or national security reasons. Although our data only covers a subset of Chinese service trading partners, the selected 45 sample trading partners actually represent a mix of major partner countries such as the US, Japan, South Korea, and Singapore, as well as smaller partner countries like Slovenia, Croatia, Malta, and Belarus. The level of air connectivity between China and the 45 countries also varies significantly, with some highly connected countries like Japan and the US and some countries without direct flight connections like Ireland and Serbia. Such significant heterogeneity among our sample countries could somewhat justify the validity of our empirical estimations. If more complete data becomes available later on, future research could consider expanding the dataset to encompass all the countries with service trade with China to provide more generalized research findings. All of these limitations stated here suggest meaningful directions for extending the current research in the future.

In study 4, we find that OSAs have significant positive impacts on transport and travel service trades as targeted by the US Department of Transportation. On the other hand, OSAs have a significant positive effect on US commercial service imports while being not significant for commercial service exports. The reasons why our results show a strong positive OSA impact on commercial service imports while being insignificant on commercial service exports are as follows: (a) Even before OSA signing, most US commercial service traders were able to travel all over the world despite the high cost of air travel. As a result, there was a more significant increase in incoming traffic from the bilateral partners to the US; (b). In addition, as more US traders traveled to smaller cities in the partner countries, they were able to find cheaper sources to import from the smaller cities than just importing from the hub cities. (c). The US exports are more concentrated in intellectual property, software, financial services, etc., which are less affected by OSAs. Furthermore, the study reveals that the mechanisms through which OSAs influence imports and exports differ. OSAs affect service exports by influencing seat capacity, while the number of direct routes plays a role in influencing service imports. An important finding is that there exists a significant positive one-year lead effect as well as three-year lag effects of OSAs on bilateral service exports and imports. In our opinion, leaving out lag and lead effects on service trade modeling would be committing an important model specification error, which would bias the empirical results.

In study 5, the results from the empirical model show that improved air connectivity significantly reduces the manufacturing firm's SO_2 emissions by enhancing their desulfurization capabilities and reducing emissions generated during production. Such impacts are found to be larger when the city is connected to more domestic major cities. The health impact of the improved air quality has also been quantified. This study provides important empirical evidence that air connectivity benefits not only a city's economic development but also its environmental sustainability as well as human health. This study also provides evidence that innovation driven by air connections is an effective channel for firms to achieve technological advancements and reduce pollution emissions. The health impact of such emission reductions is significant, potentially saving thousands of lives.

There are several limitations to study 5 that restrict the generalization of its results. The most obvious limitation is that the sample focuses solely on China, which may differ from the situation in developed countries. Additionally, this study concentrates on the emission reduction impact of air connectivity rather than exploring green innovation or patents driven by air connections. Another limitation is the research period, with the latest data being from 2013. However, given the data availability and our research question, we believe our findings are robust. Future research could focus on the innovative mechanisms of air connections for manufacturing firms and use more recent data to verify the impacts.

Appendixes

Appendix A

Supplements for Chapter 2.1

Table A1 The rank of city air passenger traffic

City name	Average monthly passenger traffic	Rank	Density
Shanghai	6600064	1	1
Beijing	6156343	2	1
Guangzhou	4210870	3	1
Chengdu	3876507	4	1
Shenzhen	3870414	5	1
Xi’an	3445219	6	2
Kunming	3288065	7	2
Chongqing	3280827	8	2
Hangzhou	2781581	9	2
Nanjing	2139854	10	3
Zhengzhou	2042609	11	3
Xiamen	1914286	12	3
Urumqi	1825664	13	3
Wuhan	1825325	14	3
Haikou	1825002	15	3
Changsha	1804628	16	3
Qingdao	1668329	17	3
Guiyang	1649532	18	3
Tianjin	1594672	19	3
Harbin	1564163	20	3
Sanya	1520670	21	3
Dalian	1437382	22	3
Shenyang	1399471	23	3

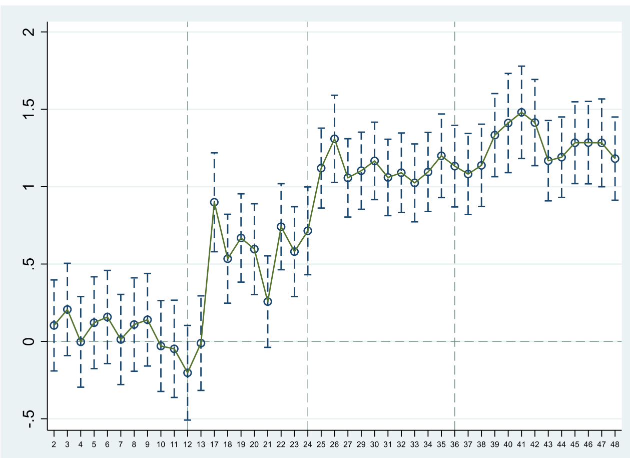
Note: The monthly average traffic is based on January 2019 to December 2019.

Table A2 Estimation results of the first stage regressions

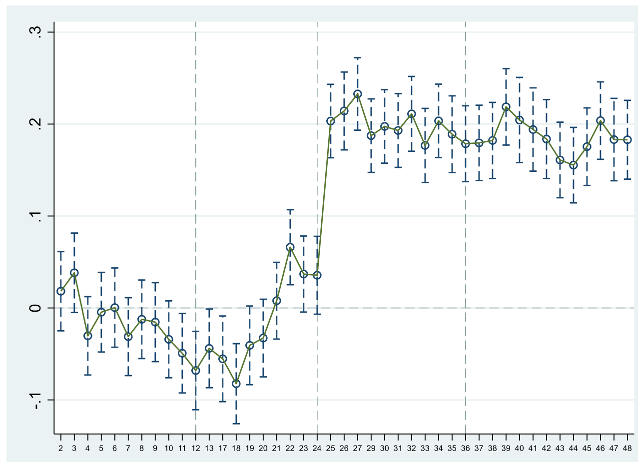
VARIABLES	lnAirport_HHI	lnRoute_HHI
lnIV_Route_HHI	0.0390***	0.996***
	(0.000150)	(7.11e-05)
lnGMEANPOP	-0.0771***	-0.000587***

	(0.00110)	(0.000215)
Control Variables	Y	Y
Carrier FE	Y	Y
Departure city FE	Y	Y
Arrival city FE	Y	Y
OD Route FE	Y	Y
Observations	8,361,559	8,361,559

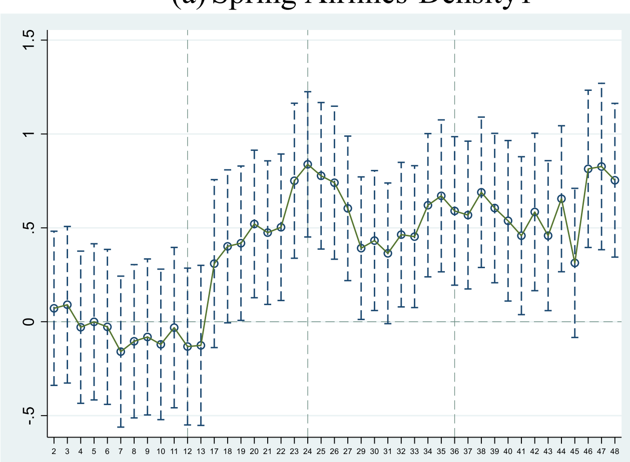
Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Standard errors in parentheses.
2. The coefficients of control variables are not listed here, and variable list is the same as Table 2.1.3.



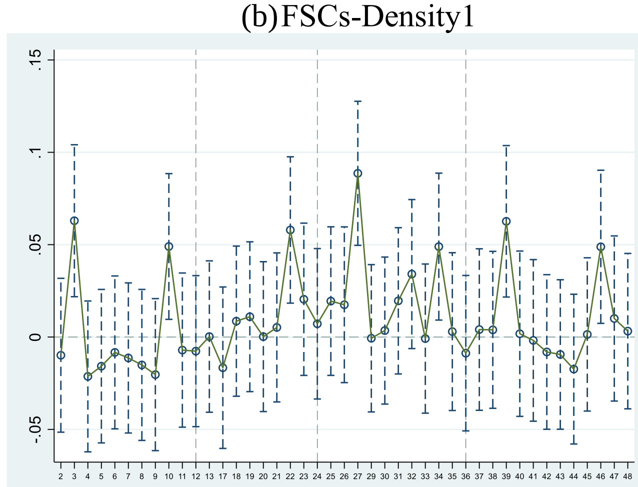
(a) Spring Airlines-Density1



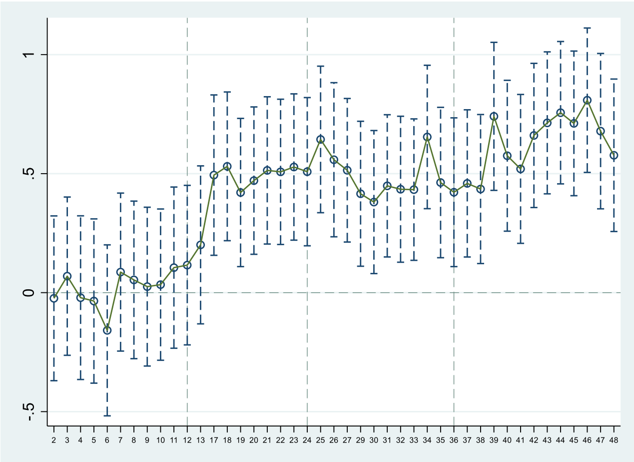
(b) FSCs-Density1



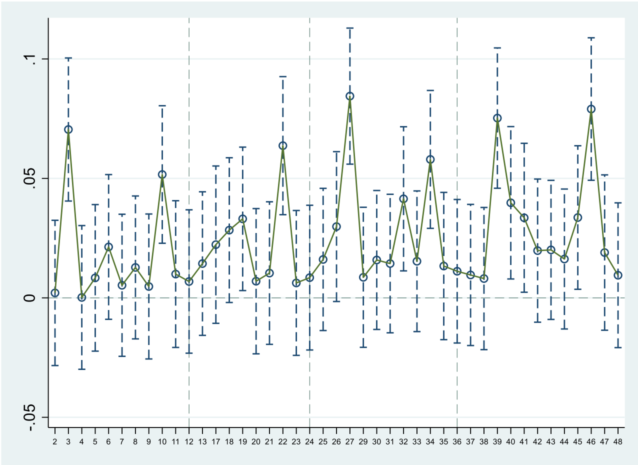
(c) Spring Airlines-Density2



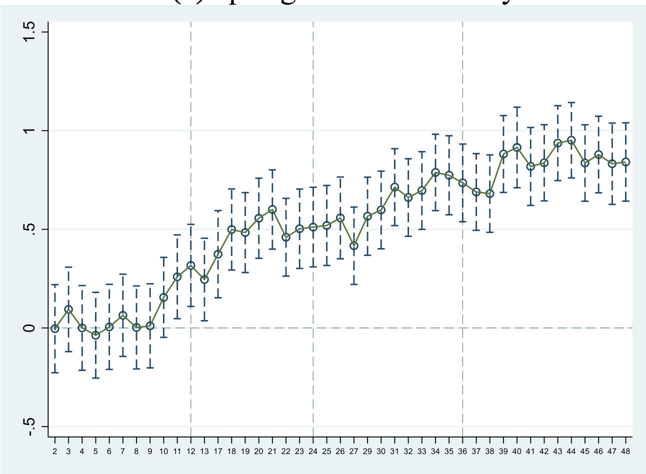
(d) FSCs -Density2



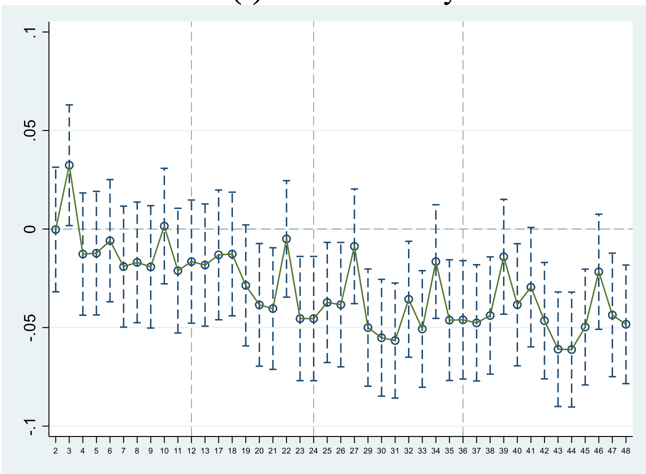
(e) Spring Airlines-Density3



(f) FSCs -Density3



(g) Spring Airlines-Others



(h) FSCs -Others

Fig. A1: The plot of the time-series effects of the route entry behaviors for Spring Airlines and FSCs on different categories of the routes

Notes:

1. The numbers 2-48 on the x-axis represent the time period from February 2019 to December 2022. January 2019 is the baseline month.
2. The impact of the pandemic occurred in the 13th month, which is January 2020.
3. The coefficients for months 14, 15, and 16 are missing. This is due to the data being dropped during the period of February 2020 to April 2020.
4. The dashed line in the graph represents the 95% confidence interval for the coefficients.

Table A3(a) The estimated effects of the pandemic on route choices (robustness test)

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	0.083^{***}	-0.242^{***}
		(0.0038)	(0.0320)
	Density2	0.008^{***}	0.031^{*}
		(0.0020)	(0.0172)
	Density3	0.016^{***}	-0.044^{***}
		(0.0017)	(0.0143)
	Others	0.019^{***}	-0.030^{*}
		(0.0019)	(0.0166)

The effect of the pandemic on FSCs route choice	Density1	-0.001	-0.023^{***}
		(0.0011)	(0.0091)
	Density2	-0.007^{***}	0.029^{***}
		(0.0006)	(0.0041)
	Density3	-0.008^{***}	0.028^{***}
		(0.0006)	(0.0038)
	Others	0.004^{***}	-0.011^{***}
		(0.0005)	(0.0025)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	0.084^{***}	-0.218^{***}
		(0.0037)	(0.0310)
	Density2	0.015^{***}	0.002
		(0.0020)	(0.0173)
	Density3	0.024^{***}	-0.071^{***}
		(0.0017)	(0.0144)
	Others	0.015^{***}	-0.019
		(0.0019)	(0.0166)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. We change the routes classification such that Density1 routes refers to routes connected with three hub airports (Beijing, Shanghai, Guangzhou), Density2 routes for endpoint airports involving the 4th-10th cities, Density3 routes for endpoint airports involving 11th-20th cities, those remaining routes are categorized as Others.
3. The observation number for this estimation is 8,361,559.

Table A3(b) The coefficients of multinomial discrete choice model (robustness test)

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	0.488^{***}	0.410
		(0.090)	(0.684)
	Density2	0.611^{***}	-2.815^{***}
		(0.100)	(0.847)
	Density3	0.690^{***}	-2.322^{***}
		(0.112)	(0.897)
	Others	0.643^{***}	-1.896^{***}
		(0.044)	(0.353)
Overlap before and after the outbreak of the pandemic	Density1	2.349^{***}	-8.637^{***}
		(0.073)	(0.543)
	Density2	0.624^{***}	-0.599
		(0.066)	(0.507)
	Density3	1.139^{***}	-4.516^{***}
		(0.084)	(0.703)
	Others	0.468^{***}	-0.282
		(0.048)	(0.394)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. We change the routes classification such that Density1 routes refers to routes connected with three hub airports (Beijing, Shanghai, Guangzhou), Density2 routes for endpoint airports involving the 4th-10th

cities, Density3 routes for endpoint airports involving 11th-20th cities, those remaining routes are categorized as Others.

3. The observation number for this estimation is 261,912.

Table A4(a) The estimated effects of the pandemic on route choices (robustness test)

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	0.241^{***}	-1.208^{***}
		(0.038)	(0.309)
	Density2	0.155^{***}	-0.661^{***}
		(0.013)	(0.106)
	Density3	0.056^{***}	-0.127^{***}
		(0.004)	(0.035)
	Others	0.015^{***}	-0.009
		(0.001)	(0.009)
The effect of the pandemic on FSCs route choice	Density1	0.018^{***}	-0.168^{**}
		(0.006)	(0.053)
	Density2	0.026^{***}	-0.066^{***}
		(0.002)	(0.022)
	Density3	0.011^{***}	-0.006
		(0.001)	(0.007)
	Others	-0.006^{***}	0.025^{***}
		(0.0003)	(0.002)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	0.223^{***}	-1.040^{***}
		(0.038)	(0.311)
	Density2	0.128^{***}	-0.595^{***}
		(0.013)	(0.107)
	Density3	0.045^{***}	-0.121^{***}
		(0.004)	(0.035)
	Others	0.022^{***}	-0.035^{***}
		(0.001)	(0.009)

Notes:

1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. We change the routes classification based on the route-level passenger volume, measured by the average monthly passenger volume of routes in 2019. We use K-means clustering to classify routes into 4 categories.
3. The observation number for this estimation is 8,361,559.

Table A4(b) The coefficients of multinomial discrete choice model (robustness test)

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	-5.144^{*}	30.554^{**}
		(2.987)	(13.249)
	Density2	14.045	10.827
		(5325)	(12.013)
	Density3	-2.792^{***}	13.131^{**}
		(0.896)	(5.443)

	Others	0.662^{***}	-2.048^{***}
		(0.035)	(0.277)
Overlap before and after the outbreak of the pandemic	Density1	3.194^{***}	-21.429^{***}
		(0.405)	(3.727)
	Density2	2.490^{***}	-12.513^{***}
		(0.153)	(1.279)
	Density3	1.143^{***}	-3.309^{***}
		(0.064)	(0.499)
	Others	0.746^{***}	-1.891^{***}
		(0.037)	(0.300)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. We change the routes classification based on the route-level passenger volume, measured by the average monthly passenger volume of routes in 2019. We use K-means clustering to classify routes into 4 categories.
3. The observation number for this estimation is 261,912.

Table A5(a) The estimated effects of the pandemic on route choices (robustness test)

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	0.049^{***}	-0.589^{***}
		(0.0022)	(0.0942)
	Density2	0.010^{***}	0.014
		(0.0021)	(0.0859)
	Density3	0.011^{***}	0.005
		(0.0014)	(0.0572)
	Others	0.020^{***}	-0.193^{***}
		(0.0017)	(0.0685)
The effect of the pandemic on FSCs route choice	Density1	-0.0004	-0.059^{**}
		(0.0006)	(0.0273)
	Density2	-0.007^{***}	0.094^{***}
		(0.0006)	(0.0185)
	Density3	-0.007^{***}	0.074^{***}
		(0.0004)	(0.0129)
	Others	0.004^{***}	-0.052^{***}
		(0.0004)	(0.0090)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	0.050^{***}	-0.530^{***}
		(0.0022)	(0.0916)
	Density2	0.018^{***}	-0.079
		(0.0021)	(0.0866)
	Density3	0.018^{***}	-0.069
		(0.0014)	(0.0575)
	Others	0.016^{***}	-0.141^{**}
		(0.0016)	(0.0684)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.

2. The variable form for attenuating effect is $\frac{1}{(COVID19_{t_t})^2}$, and the classification of Density remains the same with Section 2.1.5.
3. The observation number for this estimation is 8,361,559.

Table A5(b) The coefficients of multinomial discrete choice model (robustness test)

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	0.564^{***}	-2.678
		(0.069)	(2.538)
	Density2	0.388^{***}	-3.371
		(0.110)	(4.212)
	Density3	0.328^{***}	2.060
		(0.088)	(3.055)
	Others	0.574^{***}	-6.243^{***}
		(0.040)	(1.491)
Overlap before and after the outbreak of the pandemic	Density1	1.539^{***}	-23.964^{***}
		(0.053)	(1.996)
	Density2	0.605^{***}	-3.349
		(0.077)	(2.846)
	Density3	0.740^{***}	-5.885^{**}
		(0.063)	(2.374)
	Others	0.440^{***}	-0.228
		(0.043)	(1.681)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. The variable form for attenuating effect is $\frac{1}{(COVID19_{t_t})^2}$, and the classification of Density remains the same with Section 2.1.5.
3. The observation number for this estimation is 261,912.

Table A6(a) The estimated effects of the pandemic on route choices (robustness test)

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	0.066^{***}	-0.085^{***}
		(0.0046)	(0.0150)
	Density2	0.006	0.011
		(0.0039)	(0.0133)
	Density3	0.008^{***}	0.006
		(0.0027)	(0.0090)
	Others	0.026^{***}	-0.031^{***}
		(0.0032)	(0.0107)
The effect of the pandemic on FSCs route choice	Density1	0.001	-0.007
		(0.0017)	(0.0051)
	Density2	-0.016^{***}	0.030^{***}
		(0.0011)	(0.0031)

	Density3	-0.014^{***}	0.026^{***}
		(0.0009)	(0.0023)
	Others	0.005^{***}	-0.007^{***}
		(0.0007)	(0.0016)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	0.066^{***}	-0.079^{***}
		(0.0043)	(0.0144)
	Density2	0.022^{***}	-0.019
		(0.0039)	(0.0134)
	Density3	0.023^{***}	-0.020^{**}
		(0.0026)	(0.0089)
	Others	0.021^{***}	-0.024^{**}
		(0.0031)	(0.0106)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. The variable form for attenuating effect is $\frac{1}{\sqrt{COVID19_{tt}}}$, and the classification of Density remains the same with Section 2.1.5.
3. The observation number for this estimation is 8,361,559.

Table A6(b) The coefficients of the multinomial discrete choice model (robustness test)

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	0.829^{***}	-1.119^{***}
		(0.118)	(0.389)
	Density2	0.475^{**}	-0.443
		(0.187)	(0.615)
	Density3	0.360^{**}	-0.061
		(0.148)	(0.481)
	Others	0.945^{***}	-1.683^{***}
		(0.066)	(0.221)
Overlap before and after the outbreak of the pandemic	Density1	2.353^{***}	-3.899^{***}
		(0.086)	(0.276)
	Density2	0.818^{***}	-0.938^{**}
		(0.131)	(0.430)
	Density3	1.087^{***}	-1.554^{***}
		(0.106)	(0.353)
	Others	0.531^{***}	-0.372
		(0.074)	(0.249)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. The variable form for attenuating effect is $\frac{1}{\sqrt{COVID19_{tt}}}$, and the classification of Density remains the same with Section 2.1.5.
3. The observation number for this estimation is 261,912.

Table A7(a) The estimated effects of the pandemic on route choices (placebo test)

	Route type	Persistent effect	Attenuating effect
The effect of the pandemic on Spring Airlines route choice	Density1	−0.009	0.007
		(0.006)	(0.006)
	Density2	0.005	−0.001
		(0.005)	(0.005)
	Density3	−0.0002	0.002
		(0.003)	(0.005)
	Others	0.005	−0.003
		(0.004)	(0.005)
The effect of the pandemic on FSCs route choice	Density1	−0.003	0.002
		(0.003)	(0.004)
	Density2	0.002*	−0.001
		(0.001)	(0.001)
	Density3	−0.0002	0.002
		(0.001)	(0.004)
	Others	−0.0004	0.001
		(0.0007)	(0.004)
The different effect of the pandemic on Spring Airlines vs. FSCs	Density1	−0.006	0.006
		(0.005)	(0.005)
	Density2	0.002	0.0002
		(0.005)	(0.005)
	Density3	0.0000	0.0001
		(0.003)	(0.004)
	Others	0.005	−0.004
		(0.004)	(0.004)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. The sample for this estimation covers the period from January 2019 to December 2019, assuming that the simulated pandemic shock occurred in July 2019.
3. The variable forms for attenuating effect and persistent effect, and the classification of Density remain the same with Section 2.1.5.
4. The observation number for this estimation is 2,248,471.

Table A7(b) The coefficients of the multinomial discrete choice model (placebo test)

Base case as *FSC monopoly* routes	Route type	Persistent effect	Attenuating effect
Spring Airlines monopoly routes before and after the outbreak of the pandemic	Density1	0.084	−0.020
		(0.202)	(0.203)
	Density2	−0.402	−0.013
		(0.320)	(0.320)
	Density3	0.331	−0.156
		(0.264)	(0.267)
	Others	0.142	−0.109
		(0.121)	(0.120)
Overlap before and after the outbreak of the pandemic	Density1	−0.318**	0.242
		(0.157)	(0.160)
	Density2	0.243	−0.068
		(0.224)	(0.224)

Density3	0.040	−0.028
	(0.185)	(0.186)
Others	0.092	−0.104
	(0.125)	(0.126)

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses.
2. The sample for this estimation covers the period from January 2019 to December 2019, assuming that the simulated pandemic shock occurred in July 2019.
3. The variable forms for attenuating effect and persistent effect, and the classification of Density remain the same with Section 2.1.5.
4. The observation number for this estimation is 65,991.

Table A8 Estimation results of the linear probability model with subsample data (robustness test)

VARIABLES	Y
lnAirport_HHI	-0.849***
	(0.078)
lnAirportVol	-1.438***
	(0.027)
lnRoute_HHI	-0.172***
	(0.038)
OwnHub	-0.004
	(0.011)
Density1LCC	0.126***
	(0.026)
Density2LCC	0.102
	(0.093)
Density3LCC	0.165***
	(0.045)
OthersLCC	0.115***
	(0.030)
Constant	37.284***
	(0.683)
Observations	4,416
Departure city FE	Y
Arrival city FE	Y
OD Route FE	Y

Notes:
1. *, **, *** represent the 10%, 5% and 1% significance levels. Robust standard errors in parentheses
2. We estimate the persistent effect on airline route service by utilizing a subsample in December 2019 and December 2022. In the estimation model, if the route is newly entered by the airlines, the binary variable Y is equal to 1. If the route is not re-entered by the same airline, the binary variable is equal to 0.

3. This estimation did not use IV for that we used control variables calculated using December 2019 data. The coefficients for $Density_i$ and route distance are not reported for that they are absorbed by the route fixed effects.
4. The classification of Density remains the same with Section 2.1.5.

Appendix B

Supplements for Chapter 2.2

Table B1 Gini index of the degree centrality before (Q3 2019) and during late stage of pandemic (Q3 2022) for MASs (other than top 10 MASs)

			Domestic			International		
Rank	MAS	Region	Before	Late Stage	Diff%	Before	Late Stage	Diff%
11	Moscow	Europe	0.017	0.038	118%	0.116	0.080	-31%
12	Dubai	Latin America & Middle East	0.000	0.000	NA	0.223	0.224	0%
13	Seoul	Asia-Pacific	0.250	0.389	56%	0.464	0.480	3%
14	Dallas	North America	0.256	0.226	-12%	0.500	0.500	0%
15	San Francisco	North America	0.138	0.214	55%	0.387	0.437	13%
16	Amsterdam	Europe	0.133	0.000	-100%	0.389	0.345	-11%
17	Frankfurt	Europe	0.500	0.500	0%	0.395	0.380	-4%
18	Washington	North America	0.040	0.053	34%	0.438	0.433	-1%
19	Sao Paulo	Latin America & Middle East	0.106	0.164	55%	0.583	0.623	7%
20	Miami	North America	0.087	0.007	-92%	0.145	0.147	2%
21	Barcelona	Europe	0.667	0.586	-12%	0.403	0.426	6%
22	Houston	North America	0.180	0.150	-17%	0.359	0.361	1%
23	Rome	Europe	0.462	0.423	-8%	0.281	0.330	17%
24	Toronto	North America	0.381	0.292	-23%	0.603	0.604	0%
25	Taipei	Asia-Pacific	0.500	0.500	0%	0.407	0.442	9%
26	Osaka	Asia-Pacific	0.294	0.226	-23%	0.667	0.667	0%
27	Milan	Europe	0.026	0.062	137%	0.320	0.267	-17%
28	Mexico City	Latin America & Middle East	0.398	0.357	-10%	0.500	0.500	0%
29	Boston	North America	0.381	0.384	1%	0.642	0.667	4%
30	Dusseldorf	Europe	0.513	0.437	-15%	0.352	0.307	-13%
31	Orlando	North America	0.051	0.057	11%	0.312	0.438	40%
32	Manchester	Europe	0.292	0.232	-20%	0.278	0.271	-3%
33	Vienna	Europe	0.500	0.300	-40%	0.272	0.302	11%
34	Brussels	Europe	0.000	0.000	NA	0.383	0.319	-17%
35	Detroit	North America	0.451	0.394	-13%	0.500	0.433	-13%
36	Melbourne	Asia-Pacific	0.409	0.435	6%	0.477	0.500	5%

37	Copenhagen	Europe	0.167	0.125	-25%	0.405	0.377	-7%
38	San Diego	North America	0.142	0.132	-7%	0.318	0.500	57%
39	Philadelphia	North America	0.444	0.418	-6%	0.500	0.467	-7%
40	Oslo	Europe	0.372	0.353	-5%	0.309	0.284	-8%
41	Stockholm	Europe	0.419	0.396	-6%	0.484	0.590	22%
42	Vancouver	North America	0.304	0.394	29%	0.485	0.500	3%
43	Glasgow	Europe	0.346	0.349	1%	0.363	0.411	13%
44	Buenos Aires	Latin America & Middle East	0.255	0.110	-57%	0.456	0.125	-73%
45	Rio De Janeiro	Latin America & Middle East	0.095	0.056	-42%	0.500	0.500	0%
46	Tampa	North America	0.188	0.116	-38%	0.615	0.476	-23%
47	Tehran	Latin America & Middle East	0.500	0.500	0%	0.500	0.479	-4%
48	Stuttgart	Europe	0.357	0.389	9%	0.260	0.223	-14%
49	Venice	Europe	0.111	0.382	244%	0.230	0.142	-38%
50	Cleveland	North America	0.339	0.266	-21%	0.500	0.500	0%
51	Pisa	Europe	0.269	0.188	-30%	0.216	0.228	6%
52	Belfast	Europe	0.052	0.094	81%	0.438	0.469	7%
53	Norfolk	North America	0.403	0.474	18%	0.000	0.000	NA

Notes:
1. The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Table B2 Gini index of the traffic before (Q3 2019) and during late stage of pandemic (Q3 2022) for MASs (other than top 10 MASs)

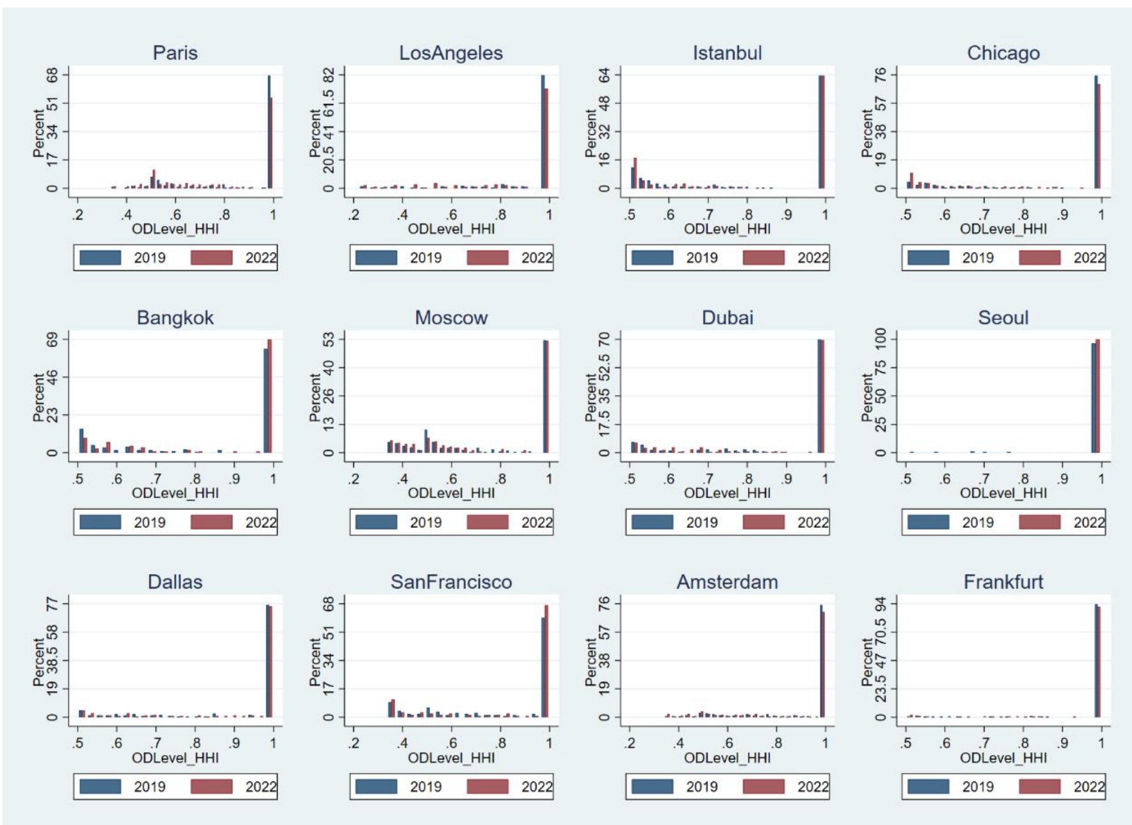
Rank	MAS	Region	Domestic			International		
			Before	Late stage	Diff%	Before	Late stage	Diff%
11	Moscow	Europe	0.155	0.201	30%	0.276	0.034	-88%
12	Dubai	Latin America & Middle East	0.000	0.000	NA	0.384	0.359	-7%
13	Seoul	Asia-Pacific	0.465	0.500	8%	0.444	0.484	9%
14	Dallas	North America	0.287	0.288	0%	0.500	0.500	0%
15	San Francisco	North America	0.274	0.222	-19%	0.569	0.606	7%
16	Amsterdam	Europe	0.552	0.173	-69%	0.568	0.543	-4%
17	Frankfurt	Europe	0.500	0.500	0%	0.481	0.472	-2%
18	Washington	North America	0.108	0.128	19%	0.528	0.527	0%
19	Sao Paulo	Latin America & Middle East	0.198	0.151	-24%	0.618	0.612	-1%

20	Miami	North America	0.057	0.047	-17%	0.189	0.215	14%
21	Barcelona	Europe	0.667	0.662	-1%	0.574	0.571	-1%
22	Houston	North America	0.192	0.194	1%	0.438	0.418	-5%
23	Rome	Europe	0.486	0.473	-3%	0.382	0.400	5%
24	Toronto	North America	0.551	0.547	-1%	0.632	0.634	0%
25	Taipei	Asia-Pacific	0.500	0.500	0%	0.441	0.467	6%
26	Osaka	Asia-Pacific	0.317	0.298	-6%	0.667	0.667	0%
27	Milan	Europe	0.335	0.150	-55%	0.444	0.293	-34%
28	Mexico City	Latin America & Middle East	0.478	0.479	0%	0.500	0.500	0%
29	Boston	North America	0.542	0.543	0%	0.661	0.667	1%
30	Dusseldorf	Europe	0.524	0.567	8%	0.492	0.456	-7%
31	Orlando	North America	0.432	0.444	3%	0.467	0.494	6%
32	Manchester	Europe	0.385	0.279	-27%	0.447	0.454	2%
33	Vienna	Europe	0.500	0.497	-1%	0.428	0.431	1%
34	Brussels	Europe	0.000	0.000	NA	0.511	0.466	-9%
35	Detroit	North America	0.484	0.482	0%	0.500	0.499	0%
36	Melbourne	Asia-Pacific	0.471	0.480	2%	0.462	0.500	8%
37	Copenhagen	Europe	0.116	0.193	67%	0.470	0.468	0%
38	San Diego	North America	0.241	0.152	-37%	0.416	0.500	20%
39	Philadelphia	North America	0.472	0.459	-3%	0.500	0.494	-1%
40	Oslo	Europe	0.466	0.468	1%	0.411	0.403	-2%
41	Stockholm	Europe	0.473	0.510	8%	0.586	0.631	8%
42	Vancouver	North America	0.424	0.414	-2%	0.498	0.500	0%
43	Glasgow	Europe	0.384	0.341	-11%	0.371	0.415	12%
44	Buenos Aires	Latin America & Middle East	0.414	0.329	-21%	0.471	0.172	-63%
45	Rio De Janeiro	Latin America & Middle East	0.102	0.315	208%	0.500	0.500	0%
46	Tampa	North America	0.508	0.458	-10%	0.666	0.654	-2%

47	Tehran	Latin America & Middle East	0.500	0.500	0%	0.500	0.500	0%
48	Stuttgart	Europe	0.463	0.480	4%	0.391	0.347	-11%
49	Venice	Europe	0.172	0.426	148%	0.355	0.282	-21%
50	Cleveland	North America	0.426	0.448	5%	0.500	0.500	0%
51	Pisa	Europe	0.265	0.320	21%	0.128	0.102	-21%
52	Belfast	Europe	0.090	0.091	1%	0.437	0.457	5%
53	Norfolk	North America	0.405	0.467	15%	0.000	0.000	NA

Notes:

1. The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.



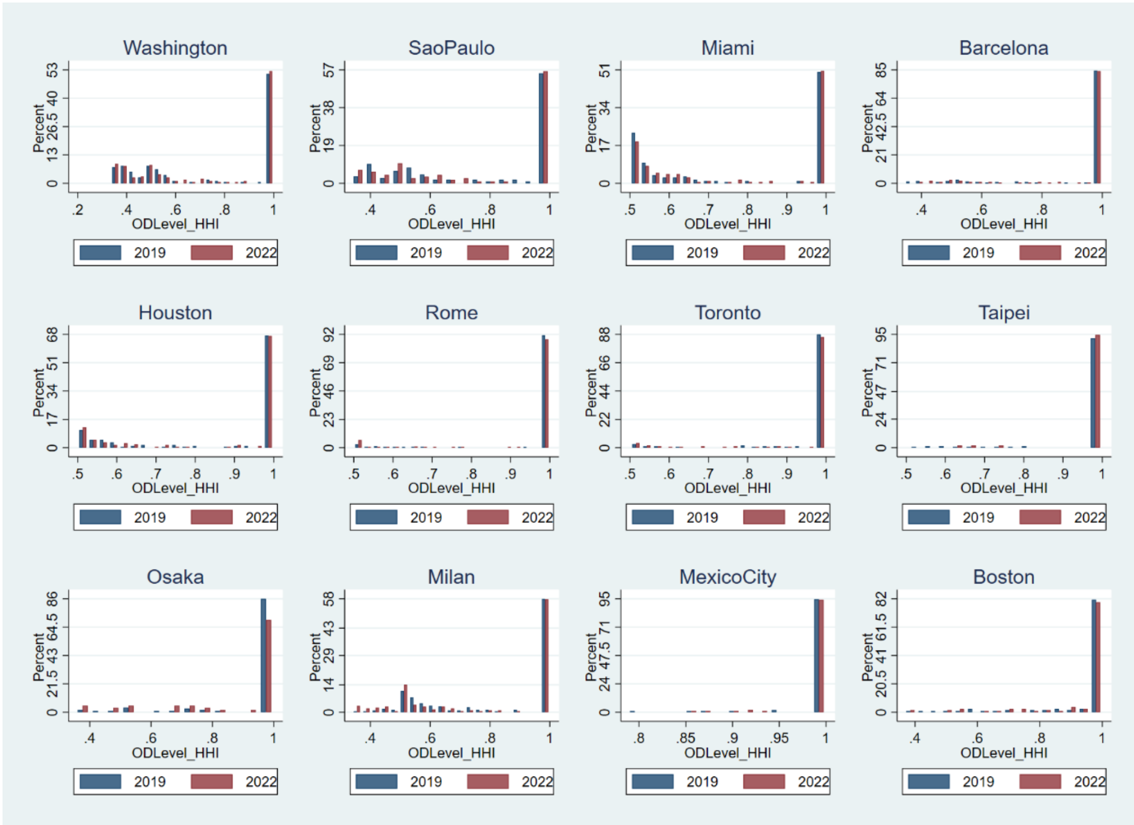


Fig.B1: The distribution of OD HHI in top 29 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 5 MASs)

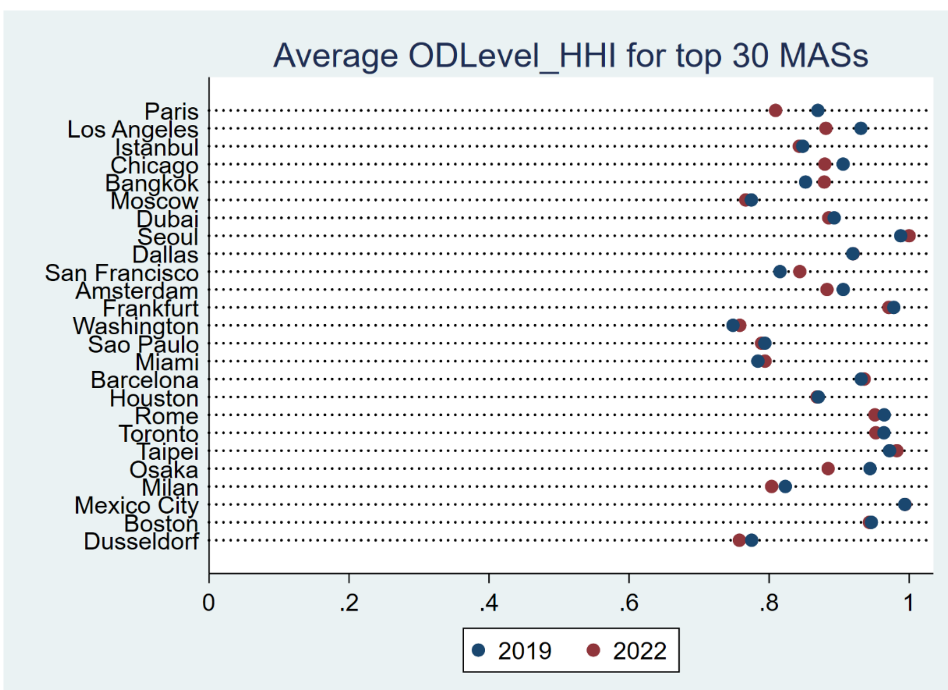


Fig. B2: The Average OD level HHI for top 30 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 5 MASs)

Table B3 Airline HHI of MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 10 MASs)

Rank	MAS	Region	Before	Late stage	Diff%
11	Moscow	Europe	0.205	0.200	-3%
12	Dubai	Latin America & Middle East	0.372	0.282	-24%
13	Seoul	Asia-Pacific	0.119	0.126	6%
14	Dallas	North America	0.504	0.491	-2%
15	San Francisco	North America	0.180	0.196	9%
16	Amsterdam	Europe	0.201	0.203	1%
17	Frankfurt	Europe	0.362	0.334	-8%
18	Washington	North America	0.190	0.197	4%
19	Sao Paulo	Latin America & Middle East	0.274	0.280	2%
20	Miami	North America	0.198	0.211	6%
21	Barcelona	Europe	0.177	0.206	16%
22	Houston	North America	0.372	0.353	-5%
23	Rome	Europe	0.155	0.126	-19%
24	Toronto	North America	0.316	0.267	-15%
25	Taipei	Asia-Pacific	0.108	0.200	84%
26	Osaka	Asia-Pacific	0.095	0.204	115%
27	Milan	Europe	0.107	0.143	35%
28	Mexico City	Latin America & Middle East	0.217	0.283	30%
29	Boston	North America	0.140	0.158	13%
30	Dusseldorf	Europe	0.154	0.150	-3%
31	Orlando	North America	0.106	0.113	7%
32	Manchester	Europe	0.116	0.146	26%
33	Vienna	Europe	0.194	0.264	36%
34	Brussels	Europe	0.156	0.153	-2%
35	Detroit	North America	0.553	0.531	-4%
36	Melbourne	Asia-Pacific	0.187	0.220	18%
37	Copenhagen	Europe	0.147	0.121	-17%
38	San Diego	North America	0.151	0.159	6%
39	Philadelphia	North America	0.460	0.398	-13%
40	Oslo	Europe	0.243	0.217	-11%
41	Stockholm	Europe	0.154	0.127	-18%
42	Vancouver	North America	0.255	0.247	-3%
43	Glasgow	Europe	0.117	0.160	37%
44	Buenos Aires	Latin America & Middle East	0.282	0.301	7%
45	Rio De Janeiro	Latin America & Middle East	0.319	0.273	-15%

46	Tampa	North America	0.155	0.155	0%
47	Tehran	Latin America & Middle East	0.129	0.114	-12%
48	Stuttgart	Europe	0.154	0.181	17%
49	Venice	Europe	0.086	0.143	66%
50	Cleveland	North America	0.164	0.159	-4%
51	Pisa	Europe	0.153	0.201	31%
52	Belfast	Europe	0.298	0.405	36%
53	Norfolk	North America	0.258	0.227	-12%

Notes:

1. The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Table B4 Gini index of LCC capacity share in MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 10 MASs)

Rank	MAS	Region	Before	Late stage	Diff%
11	Moscow	Europe	0.648	0.608	-6%
12	Dubai	Latin America & Middle East	0.341	0.271	-20%
13	Seoul	Asia-Pacific	0.031	0.114	264%
14	Dallas	North America	0.440	0.428	-3%
15	San Francisco	North America	0.329	0.309	-6%
16	Amsterdam	Europe	0.252	0.257	2%
17	Frankfurt	Europe	0.435	0.465	7%
18	Washington	North America	0.467	0.492	5%
19	Sao Paulo	Latin America & Middle East	0.207	0.244	18%
20	Miami	North America	0.464	0.341	-27%
21	Barcelona	Europe	0.084	0.044	-47%
22	Houston	North America	0.420	0.373	-11%
23	Rome	Europe	0.306	0.191	-37%
24	Toronto	North America	0.560	0.580	4%
25	Taipei	Asia-Pacific	0.420	0.500	19%
26	Osaka	Asia-Pacific	0.462	0.407	-12%
27	Milan	Europe	0.412	0.248	-40%
28	Mexico City	Latin America & Middle East	0.172	0.214	24%
29	Boston	North America	0.073	0.148	104%
30	Dusseldorf	Europe	0.150	0.160	6%
31	Orlando	North America	0.103	0.122	18%
32	Manchester	Europe	0.152	0.095	-37%
33	Vienna	Europe	0.238	0.107	-55%

34	Brussels	Europe	0.563	0.564	0%
35	Detroit	North America	0.098	0.299	205%
36	Melbourne	Asia-Pacific	0.204	0.163	-20%
37	Copenhagen	Europe	0.115	0.100	-13%
38	San Diego	North America	0.155	0.152	-2%
39	Philadelphia	North America	0.349	0.305	-12%
40	Oslo	Europe	0.069	0.140	102%
41	Stockholm	Europe	0.515	0.494	-4%
42	Vancouver	North America	0.461	0.432	-6%
43	Glasgow	Europe	0.195	0.123	-37%
44	Buenos Aires	Latin America & Middle East	0.076	0.065	-15%
45	Rio De Janeiro	Latin America & Middle East	0.033	0.122	266%
46	Tampa	North America	0.239	0.155	-35%
47	Tehran	Latin America & Middle East	0.500	0.500	0%
48	Stuttgart	Europe	0.135	0.135	0%
49	Venice	Europe	0.172	0.124	-28%
50	Cleveland	North America	0.278	0.116	-58%
51	Pisa	Europe	0.261	0.174	-33%
52	Belfast	Europe	0.500	0.404	-19%
53	Norfolk	North America	0.500	0.500	0%

Notes:
1. The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022.
2. The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Appendix C

Supplements for Chapter 3.1

Table C1 The detailed components of each type of service trade defined by UN Comtrade

Travel	Business travel, personal travel, health care, tourism, studying abroad
Transport	Water transport, air transport, land and other transport
Commercial	Maintenance and repair services, construction services, insurance services, financial services, telecommunication computer and information services, charges for the use of intellectual property, professional and management consulting services, research and development services, technical, trade-related and other business services, personal cultural and recreational services
Government	Inter-government services

Table C2 The impact of No. of direct routes on service export (random effect)

	Total export	Transport export	Travel export	Commercial export
No. of direct routes	0.263***	0.143*	0.368***	0.414***
	(0.0631)	(0.0796)	(0.0862)	(0.0974)
GDP	1.234***	1.622***	1.067***	1.471***
	(0.157)	(0.211)	(0.210)	(0.272)
Internet penetration	-0.505***	-0.128	-1.153***	-0.340
	(0.160)	(0.202)	(0.222)	(0.248)
Exchange rate	1.367***	0.234	1.209**	1.949***
	(0.350)	(0.465)	(0.482)	(0.585)
Distance	-0.578	0.111	1.712**	2.690*
	(0.471)	(0.726)	(0.801)	(1.411)
Contiguous	1.724**	0.0923	-1.796	-2.279
	(0.805)	(1.153)	(1.115)	(2.147)
Continent	0.145	1.807	4.801***	6.057**
	(0.675)	(1.385)	(1.290)	(2.783)
Landlocked	-0.00174	0.445	-1.148**	1.796***
	(0.489)	(0.669)	(0.576)	(0.591)
Common language	-0.261	-0.0702	4.084**	
	(0.934)	(1.231)	(1.844)	
RTA	0.111	-0.212	-0.0738	0.329
	(0.146)	(0.179)	(0.239)	(0.236)
LSBCI	2.087***	2.199***	1.352*	3.397***
	(0.559)	(0.705)	(0.757)	(0.903)
Constant	9.908**	-0.547	-10.51	-24.62**
	(4.577)	(6.922)	(7.428)	(12.22)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C3 The impact of route-level traffic density on service export (random effect)

	Total export	Transport export	Travel export	Commercial export
No. of passengers	0.0151	0.0323*	0.0192	0.0603**
per route	(0.0132)	(0.0175)	(0.0190)	(0.0254)
GDP per capita	1.222***	1.601***	1.125***	1.401***
	(0.161)	(0.211)	(0.215)	(0.280)
Internet penetration	-0.486***	-0.124	-1.114***	-0.388
	(0.163)	(0.202)	(0.228)	(0.257)
Exchange rate	1.403***	0.269	1.132**	2.032***
	(0.357)	(0.466)	(0.494)	(0.601)
Distance	-0.859*	0.0409	1.404*	3.311**
	(0.473)	(0.696)	(0.820)	(1.375)
Contiguous	1.776**	-0.102	-1.852	-3.790*
	(0.816)	(1.106)	(1.140)	(2.068)
Continent	0.224	2.008	5.142***	8.227***

	(0.687)	(1.318)	(1.324)	(2.654)
Landlocked	-0.0979	0.362	-1.293**	1.693***
	(0.498)	(0.648)	(0.594)	(0.601)
Common language	-0.335	-0.129	3.719**	
	(0.947)	(1.182)	(1.885)	
RTA	0.235	-0.140	0.150	0.552**
	(0.146)	(0.175)	(0.239)	(0.239)
LSBCI	2.376***	2.173***	1.812**	3.782***
	(0.575)	(0.716)	(0.793)	(0.950)
Constant	12.55***	0.232	-8.301	-29.64**
	(4.610)	(6.667)	(7.631)	(11.93)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C4 The impact of No. of direct routes on service import (random effect)

	Total import	Transport import	Travel import	Commercial import
No. of direct routes	0.405***	0.434***	0.387***	0.669***
	(0.0858)	(0.105)	(0.122)	(0.179)
GDP per capita	1.108***	0.985***	0.368	1.254***
	(0.218)	(0.274)	(0.314)	(0.438)
Internet penetration	-0.403*	-0.595**	-0.931***	-0.362
	(0.219)	(0.270)	(0.299)	(0.450)
Exchange rate	2.641***	2.888***	4.390***	3.076***
	(0.480)	(0.604)	(0.664)	(0.966)
Distance	0.00283	0.842	6.365***	1.794
	(0.570)	(0.816)	(2.272)	(1.835)
Contiguous	1.004	-1.080	-10.01***	-0.214
	(0.978)	(1.301)	(3.336)	(2.866)
Continent	0.230	3.124**	13.84***	3.262
	(0.923)	(1.563)	(4.460)	(3.693)
Landlocked	-0.535	-0.384	0.128	2.370***
	(0.615)	(0.774)	(0.879)	(0.828)
Common language	0.878	0.854	14.13***	
	(1.100)	(1.389)	(4.276)	
RTA	0.140	-0.107	0.257	0.124
	(0.202)	(0.235)	(0.320)	(0.375)
LSBCI	2.126***	1.377	1.604	4.714***
	(0.750)	(0.925)	(1.137)	(1.583)
Constant	5.230	-2.330	-46.94**	-15.72
	(5.571)	(7.894)	(20.00)	(15.78)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C5 The impact of route-level traffic density on service import (random effect)

	Total import	Transport import	Travel import	Commercial import
No. of passengers per route	0.0797***	0.0544**	0.108***	0.226***
	(0.0175)	(0.0224)	(0.0245)	(0.0407)
GDP per capita	0.931***	0.997***	0.345	1.006***
	(0.221)	(0.278)	(0.310)	(0.382)
Internet penetration	-0.365*	-0.551**	-0.905***	-0.568
	(0.216)	(0.275)	(0.296)	(0.428)
Exchange rate	2.954***	2.874***	4.425***	3.049***
	(0.480)	(0.614)	(0.655)	(0.893)
Distance	-0.408	0.651	6.641***	1.018
	(0.628)	(0.807)	(2.201)	(1.390)
Contiguous	0.808	-1.577	-11.28***	-0.465
	(1.083)	(1.288)	(3.208)	(2.171)
Continent	0.348	3.932**	15.25***	2.955
	(1.024)	(1.532)	(4.265)	(2.725)
Landlocked	-0.980	-0.576	-0.171	2.067***
	(0.670)	(0.775)	(0.862)	(0.690)
common language	0.923	0.627	14.95***	
	(1.219)	(1.376)	(4.145)	
RTA	0.340*	0.103	0.469	0.326
	(0.194)	(0.234)	(0.308)	(0.355)
LSBCI	1.653**	1.576*	1.224	5.111***
	(0.758)	(0.952)	(1.129)	(1.347)
Constant	10.73*	-0.757	-49.27**	-6.887
	(6.082)	(7.848)	(19.35)	(12.01)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C6 The impact of No. of direct routes on service import and export (SUR model)

VARIABLES	(1) Total import	(2) Transport import	(3) Travel import	(4) Commercial import	(5) Total export	(6) Transport export	(7) Travel export	(8) Commercial export
No. of direct routes	1.401**	1.725**	1.781**	2.335**	1.145**	0.609	-0.408	2.451***
	(0.696)	(0.779)	(0.761)	(1.122)	(0.519)	(0.690)	(0.517)	(0.695)
GDP per capita	0.855**	1.864***	0.280	0.870	1.282***	0.907**	0.966***	1.752***
	(0.392)	(0.438)	(0.428)	(0.632)	(0.292)	(0.389)	(0.291)	(0.391)
Exchange rate	-0.448	-0.781**	-0.856**	-1.014*	-0.446*	-0.346	-0.600**	-1.046***
	(0.322)	(0.360)	(0.352)	(0.519)	(0.240)	(0.319)	(0.239)	(0.322)
Internet penetration	3.064***	1.912**	4.031***	4.176***	0.756	0.879	1.547***	1.956***
	(0.753)	(0.842)	(0.823)	(1.214)	(0.561)	(0.746)	(0.560)	(0.752)
RTA	-0.248	-0.597	-0.280	-0.538	-0.292	-0.493	0.435	-0.691
	(0.425)	(0.476)	(0.465)	(0.686)	(0.317)	(0.421)	(0.316)	(0.425)
LSBCI	-1.479	-2.026	1.118	-3.318	0.894	3.948**	-0.969	-1.271
	(1.563)	(1.748)	(1.707)	(2.519)	(1.165)	(1.549)	(1.161)	(1.560)

Constant	9.896**	-3.771	13.75***	5.827	4.519	6.440	10.24***	-4.168
	(4.280)	(4.788)	(4.677)	(6.902)	(3.190)	(4.244)	(3.181)	(4.274)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	168	168	168	168	168	168	168
R-squared	0.973	0.968	0.979	0.932	0.977	0.965	0.987	0.965

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C7 The impact of route-level traffic density on service import and export (SUR model)

VARIABLES	(1) Total import	(2) Transport import	(3) Travel import	(4) Commercial import	(5) Total export	(6) Transport export	(7) Travel export	(8) Commercial export
No. of passengers per route	0.594**	0.731**	0.755**	0.989**	0.485**	0.258	-0.173	1.039***
	(0.295)	(0.330)	(0.322)	(0.476)	(0.220)	(0.292)	(0.219)	(0.294)
GDP per capita	0.308	1.190***	-0.416	-0.0422	0.835***	0.670	1.126***	0.795*
	(0.411)	(0.460)	(0.449)	(0.663)	(0.306)	(0.408)	(0.306)	(0.411)
Exchange rate	-0.542	-0.896**	-0.975**	-1.170**	-0.523**	-0.387	-0.573**	-1.210***
	(0.348)	(0.389)	(0.380)	(0.561)	(0.259)	(0.345)	(0.259)	(0.348)
Internet penetration	3.973***	3.030***	5.185***	5.690***	1.498***	1.273*	1.283**	3.545***
	(0.744)	(0.832)	(0.813)	(1.199)	(0.554)	(0.737)	(0.553)	(0.742)
RTA	0.521**	0.351	0.698***	0.744**	0.337**	-0.159	0.211	0.656***
	(0.213)	(0.238)	(0.232)	(0.343)	(0.159)	(0.211)	(0.158)	(0.212)
LSBCI	-4.684*	-5.972*	-2.956	-8.658**	-1.726	2.556	-0.0353	-6.878**
	(2.724)	(3.047)	(2.977)	(4.393)	(2.030)	(2.701)	(2.025)	(2.720)
Constant	9.896**	-3.771	13.75***	5.827	4.519	6.440	10.24***	-4.168
	(4.280)	(4.788)	(4.677)	(6.902)	(3.190)	(4.244)	(3.181)	(4.274)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	168	168	168	168	168	168	168
R-squared	0.973	0.968	0.979	0.932	0.977	0.965	0.987	0.965

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix D

Supplements for Chapter 3.2

Appendix D1. The OAS impact

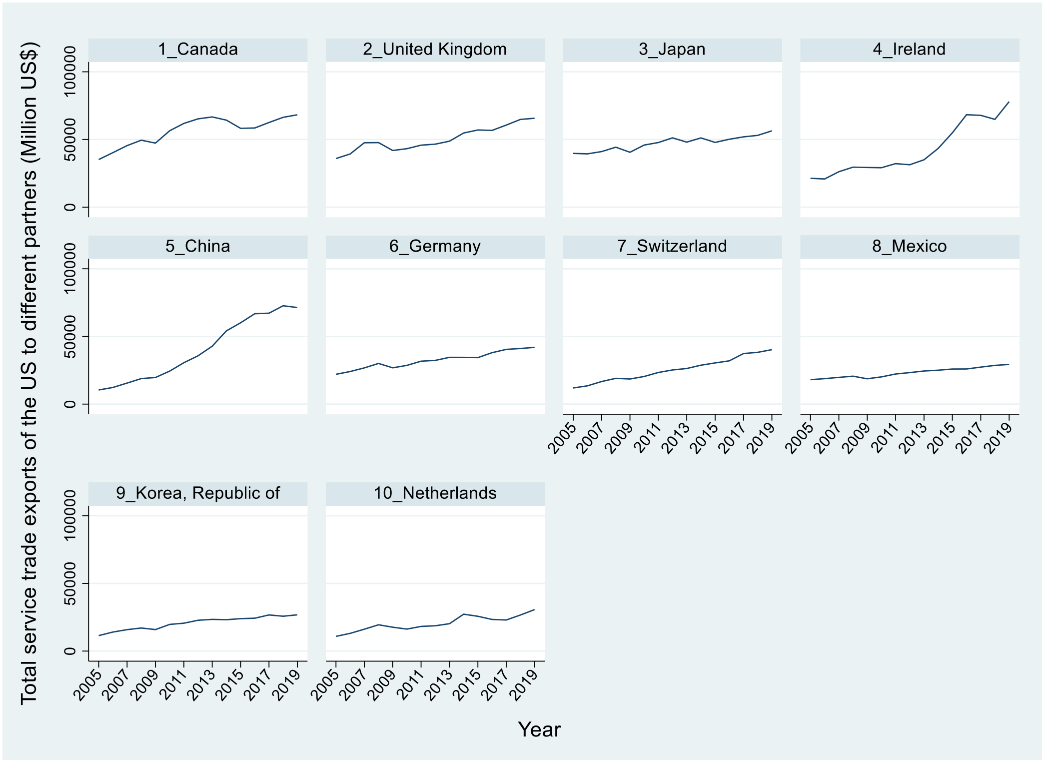


Fig. D1: Service trade exports between the US and its top 10 partners (2005–2019)
Source: Compiled by authors based on the data from the WTO Stats database.

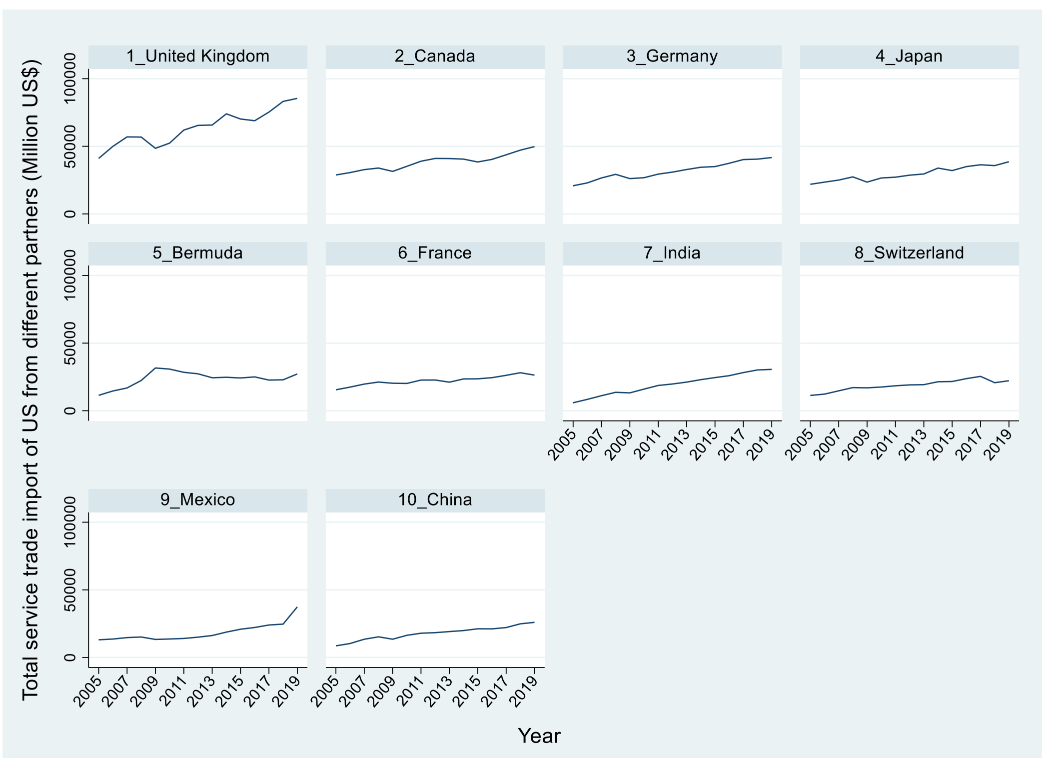


Fig. D2: Service trade imports between the US and its top 10 partners (2005–2019)
Source: Compiled by authors based on the data from the WTO Stats database.

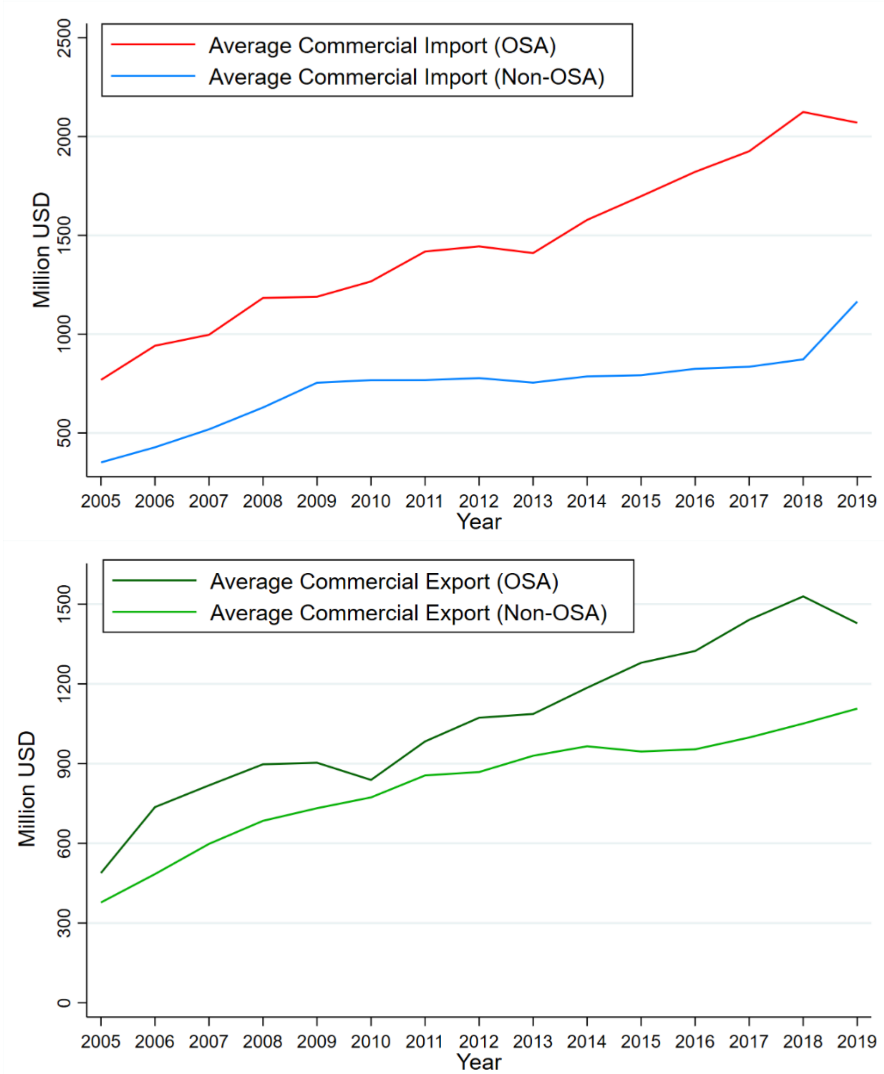


Fig. D3: Comparison of average commercial imports and exports between the US and trading partners with and without OSA

Notes: To maintain data consistency and comparability, we selected a sample of four countries that signed OSA with the US in 2010. For the non-OSA sample, we included all countries that had not signed the OSA as of 2019. It is worth noting that using OSA samples signed in other years could yield similar patterns. However, for the sake of brevity, this figure only depicts the comparison between non-OSA countries and OSA countries that signed the agreement in 2010.
Source: Compiled by authors based on the data from WTO Stats portal.

Table D1 The classification of service trade in EBOPS (2010)

	Classification:
1	Manufacturing services on physical inputs owned by others
2	Maintenance and repair services not included elsewhere (n.i.e)
3	Transport: Sea transport Air transport Other modes of transport Postal and courier services

4	Travel: 4.1 Business: Acquisition of goods and services by border, seasonal, and other short-term workers; Other (Business) 4.2 Personal: Health-related; Education-related; Other (Personal)
5	Construction
6	Insurance and pension services
7	Financial services
8	Charges for the use of intellectual property n.i.e.
9	Telecommunications, computer, and information services
10	Other business services: 10.1 Research and development services 10.2 Professional and management consulting services 10.3 Technical, trade-related and other business services
11	Personal, cultural, and recreational services
12	Government goods and services n.i.e.

Source: Manual on Statistics of International Trade in Services 2010.

Table D2 The first-stage regression results on OSA

VARIABLES	OSA
ln Common City Number	0.0560***
	(0.0176)
RTA	0.0395
	(0.0335)
LSBCI	0.302
	(0.236)
ln Internet	-0.0578***
	(0.00989)
ln Exchange Rate	-0.00513
	(0.0220)
ln GDP per Capita	-0.0715**
	(0.0292)
Observations	1,612
Year FE	Y
Country FE	Y
F-statistics	10.124

Notes:
1. The table reports the first-stage regression result from equation 3.2.2.
2. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. FE = fixed effect.
3. Time-fixed variables, such as distance, contiguous, and common language, can be controlled by the time-fixed effect. Thus, we do not include these variables in our regression analysis.
4. Although the US has signed the OSA with 126 partners, we excluded the 55 partners that do not have direct flights to the US and conducted the regression using the remaining 71 OSA countries and other 65 non-OSA countries. This approach helps to minimize bias and provides a more accurate analysis of the relationship between OSA and the service trade.

Table D3 Proportion of commercial subsector within commercial services

	Import	Export
Manufacturing services	3%	1%
Maintenance and repair services	2%	3%
Construction	1%	1%
Insurance and pension services	13%	4%
Financial services	13%	13%
Charges for the use of intellectual property	16%	29%
Telecommunications, computer, and information services	13%	8%
Other business services	37%	37%
Personal, cultural, and recreational services	2%	5%

Notes: This table reports the average proportion of commercial subsectors within commercial service exports and imports during the study period. For example, the manufacturing service import ratio is calculated by dividing the total manufacturing service imports from 136 partners by the total commercial service imports from those 136 countries in a specific year. The average ratio is then calculated over a period of 15 years (2005-2019).

Source: Compiled by authors based on the data from the WTO Stats database.

Table D4 (a) The impact of OSA on commercial service export (subsector)

Dependent variables	OSA	Control Variables	Observations	Country FE	Year FE
ln Manufacturing Export	0.0359 (0.954)	Y	1612	Y	Y
ln Maintenance Export	1.782* (1.071)	Y	1612	Y	Y
ln Construction Export	1.926 (1.179)	Y	1612	Y	Y
ln Insurance Export	1.040 (0.757)	Y	1612	Y	Y
ln Financial Export	2.507** (1.138)	Y	1612	Y	Y
ln Intellectual Property Export	0.672 (0.713)	Y	1612	Y	Y
ln Telecommunications Export	2.890** (1.127)	Y	1612	Y	Y
ln Other Business Services Export	0.973 (0.907)	Y	1612	Y	Y
ln Personal Export	-0.264 (0.616)	Y	1612	Y	Y

Note: Same as Table 3.2.3. The full names of each commercial service subsector can be found in Table D1. For brevity, the coefficients of the control variables were not reported.

Table D4(b) The impact of OSA on commercial service import

Dependent variables	OSA	Control Variables	Observations	Country FE	Year FE
ln Manufacturing Import	4.049** (1.689)	Y	1612	Y	Y
ln Maintenance Import	3.658*** (1.313)	Y	1612	Y	Y
ln Construction Import	2.921** (1.356)	Y	1612	Y	Y
ln Insurance Import	1.770* (0.974)	Y	1612	Y	Y
ln Financial Import	2.128** (1.032)	Y	1612	Y	Y
ln Intellectual Property Import	0.676 (0.790)	Y	1612	Y	Y
ln Telecommunications Import	3.468** (1.427)	Y	1612	Y	Y
ln Other Business Services Import	4.215** (1.789)	Y	1612	Y	Y
ln Personal Import	1.996** (0.956)	Y	1612	Y	Y

Note: Same as Table 3.2.3. The full names of each commercial service subsector can be found in Table D1. For brevity, the coefficients of the control variables were not reported.

Appendix D2. Lead and lag effects of OSA

Table D5(a) The two-year lead effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lead 2 years	2.181	9.545	12.792
	(3.323)	(9.736)	(14.332)
RTA	-0.034	-0.352	-0.424
	(0.115)	(0.388)	(0.540)
LSBCI	-0.163	-2.785	-3.453
	(1.392)	(4.202)	(6.148)
ln Internet	0.108	0.235	0.417
	(0.073)	(0.196)	(0.308)
ln Exchange Rate	-0.130**	-0.138	-0.399*
	(0.052)	(0.174)	(0.226)
ln GDP per Capita	0.515***	0.418**	0.551**
	(0.064)	(0.197)	(0.257)

Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. FE = fixed effect.

Table D5(b) The two-year lead effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lead 2 years	35.586	9.483	10.779
	(57.058)	(13.515)	(12.134)
RTA	-1.109	-0.223	-0.289
	(1.943)	(0.454)	(0.451)
LSBCI	-17.772	-2.902	-4.135
	(27.873)	(5.644)	(5.550)
ln Internet	0.752	0.264	0.379
	(1.142)	(0.278)	(0.248)
ln Exchange Rate	-0.028	-0.158	-0.477**
	(0.850)	(0.188)	(0.190)
ln GDP per Capita	0.742	0.365*	0.342
	(0.845)	(0.202)	(0.225)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D6(a) The one-year lead effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lead 1 year	0.819	3.748**	4.749**
	(0.983)	(1.737)	(2.309)
RTA	0.002	-0.200	-0.211
	(0.053)	(0.135)	(0.162)
LSBCI	0.394	-0.445	-0.168
	(0.489)	(1.038)	(1.328)
ln Internet	0.094**	0.193***	0.335***
	(0.044)	(0.074)	(0.101)
ln Exchange Rate	-0.113***	-0.057	-0.302***
	(0.042)	(0.079)	(0.104)
ln GDP per Capita	0.540***	0.520***	0.697***
	(0.059)	(0.116)	(0.143)
Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D6(b) The one-year lead effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lead 1 year	9.682*	3.100*	4.074*
	(4.973)	(1.878)	(2.203)
RTA	-0.367	-0.057	-0.119
	(0.346)	(0.119)	(0.149)
LSBCI	-5.400*	-0.328	-1.196
	(3.275)	(1.038)	(1.290)
ln Internet	0.440**	0.198**	0.322***
	(0.222)	(0.086)	(0.096)
ln Exchange Rate	-0.080	-0.079	-0.399***
	(0.244)	(0.082)	(0.091)
ln GDP per Capita	0.819***	0.453***	0.483***
	(0.312)	(0.115)	(0.124)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D7(a) The one-year lag effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lag 1 year	2.669***	3.345***	0.583
	(0.945)	(1.285)	(0.674)
RTA	-0.241**	-0.259**	-0.007
	(0.107)	(0.127)	(0.058)
LSBCI	0.601	1.169	0.623**
	(0.625)	(0.772)	(0.306)
ln Internet	0.209***	0.351***	0.097**
	(0.062)	(0.085)	(0.046)
ln Exchange Rate	0.031	-0.194*	-0.094*
	(0.075)	(0.099)	(0.052)
ln GDP per Capita	0.660***	0.869***	0.570***
	(0.120)	(0.157)	(0.079)
Observations	1,569	1,612	1,611
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D7(b) The one-year lag effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lag 1 year	6.125***	2.091**	2.879**
	(2.221)	(1.033)	(1.269)
RTA	-0.421*	-0.084	-0.163
	(0.243)	(0.098)	(0.122)
LSBCI	-2.262	0.543	0.025
	(1.578)	(0.588)	(0.742)
ln Internet	0.451***	0.208***	0.339***
	(0.161)	(0.076)	(0.085)
ln Exchange Rate	0.066	-0.011	-0.307***
	(0.213)	(0.083)	(0.092)
ln GDP per Capita	1.099***	0.557***	0.636***
	(0.302)	(0.125)	(0.138)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D8(a) The two-years lag effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lag 2 years	0.629	2.862***	3.603**
	(0.720)	(1.053)	(1.443)
RTA	0.003	-0.198*	-0.206*
	(0.053)	(0.106)	(0.123)
LSBCI	0.690**	0.917	1.554*
	(0.303)	(0.715)	(0.874)
ln Internet	0.103**	0.230***	0.381***
	(0.051)	(0.072)	(0.100)
ln Exchange Rate	-0.082	0.084	-0.126
	(0.062)	(0.092)	(0.121)
ln GDP per Capita	0.585***	0.728***	0.954***
	(0.093)	(0.148)	(0.196)
Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D8(b) The two-years lag effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lag 2 years	7.172**	2.246**	3.095**
	(2.928)	(1.133)	(1.401)
RTA	-0.346	-0.050	-0.117
	(0.264)	(0.091)	(0.116)
LSBCI	-1.623	0.781	0.358
	(1.864)	(0.641)	(0.806)
ln Internet	0.554**	0.228***	0.365***
	(0.217)	(0.087)	(0.097)
ln Exchange Rate	0.243	0.031	-0.250**
	(0.296)	(0.097)	(0.113)
ln GDP per Capita	1.311***	0.611***	0.708***
	(0.422)	(0.149)	(0.171)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D9(a) The three-years lag effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lag 3 years	0.764	3.446**	4.380**
	(0.876)	(1.469)	(2.033)
RTA	0.008	-0.174	-0.176
	(0.052)	(0.121)	(0.143)
LSBCI	0.873**	1.752*	2.600**
	(0.363)	(0.925)	(1.143)
ln Internet	0.112*	0.268***	0.433***
	(0.061)	(0.095)	(0.135)
ln Exchange Rate	-0.066	0.152	-0.038
	(0.077)	(0.133)	(0.176)
ln GDP per Capita	0.610***	0.844***	1.101***
	(0.120)	(0.217)	(0.291)
Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D9(b) The three-years lag effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lag 3 years	7.711**	2.744*	3.766**
	(3.259)	(1.526)	(1.908)
RTA	-0.278	-0.031	-0.092
	(0.266)	(0.096)	(0.129)
LSBCI	0.280	1.430*	1.283
	(2.065)	(0.808)	(1.023)
ln Internet	0.610**	0.262**	0.411***
	(0.244)	(0.110)	(0.126)
ln Exchange Rate	0.320	0.087	-0.173
	(0.334)	(0.132)	(0.162)
ln GDP per Capita	1.475***	0.708***	0.835***
	(0.514)	(0.210)	(0.254)
Observations	1,523	1,553	1,591
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D10(a) The four-years lag effect of OSA on service trade exports

VARIABLES	ln Commercial Export	ln Transport Export	ln Travel Export
OSA lag 4 years	1.586	7.271	9.163
	(2.190)	(6.539)	(8.874)
RTA	0.012	-0.167	-0.154
	(0.069)	(0.241)	(0.293)
LSBCI	1.408	4.220	5.699
	(1.047)	(3.303)	(4.329)
ln Internet	0.153	0.472	0.675
	(0.127)	(0.368)	(0.500)
ln Exchange Rate	0.019	0.520	0.460
	(0.204)	(0.590)	(0.823)
ln GDP per Capita	0.725**	1.366	1.769
	(0.295)	(0.883)	(1.193)
Observations	1,611	1,569	1,612
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Table D10(b) The four-year lag effect of OSA on service trade imports

VARIABLES	ln Commercial Import	ln Transport Import	ln Travel Import
OSA lag 4 years	6.004	7.927	15.399
	(6.455)	(7.758)	(13.470)
RTA	-0.013	-0.071	-0.244
	(0.192)	(0.256)	(0.508)
LSBCI	3.429	4.025	5.213
	(3.034)	(3.842)	(6.392)
ln Internet	0.429	0.620	1.031
	(0.378)	(0.435)	(0.842)
ln Exchange Rate	0.424	0.258	1.211
	(0.596)	(0.717)	(1.431)
ln GDP per Capita	1.185	1.410	2.644
	(0.879)	(1.020)	(1.978)
Observations	1,553	1,591	1,523
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Same as Table D5(a).

Appendix D3. Mechanism analysis

Table D11 The impact of OSA on air connectivity

VARIABLES	ln Average Seats per City	ln Direct City
OSA	0.545***	0.062***
	(0.202)	(0.015)
RTA	0.137	0.011
	(0.240)	(0.020)
LSBCI	2.188	0.542***
	(1.803)	(0.193)
ln Internet	0.165*	0.011
	(0.095)	(0.008)
ln Exchange Rate	0.527***	-0.011
	(0.178)	(0.017)
ln GDP per Capita	0.442*	0.026
	(0.244)	(0.023)
Observations	2,309	2,309
Country FE	Y	Y
Year FE	Y	Y

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. FE = fixed effect.

Table D12 The first-stage regression results on air connectivity

VARIABLES	ln Average Seats per City	ln Direct City
ln Common City Number	0.405***	-0.00841
	(0.137)	(0.0118)
ln Average Connect City Number	-1.085	0.449***
	(1.581)	(0.163)
RTA	0.122	0.00916
	(0.241)	(0.0202)
LSBCI	2.068	0.461**
	(1.867)	(0.192)
ln Internet	0.133	0.0167**
	(0.101)	(0.00811)
ln Exchange Rate	0.597***	-0.00722
	(0.184)	(0.0183)
ln GDP per Capita	0.290	0.0162
	(0.259)	(0.0242)
Observations	2,295	2,295
Country FE	Y	Y
Year FE	Y	Y
F-statistics	8.57	7.93

Notes:
1. This table reports the first-stage regression results of Equation 3.2.5, using two IVs, the common city number and the average connected city number.
2. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. FE = fixed effect.
3. The correlation coefficient between direct city number and average seats per city is 0.26.
4. For convenience, in our study, we do not differentiate between airports and cities, meaning that multi-airport cities are considered as multiple connections.

Appendix E

Supplements for Chapter 4

Table E1 National economic industry classification and codes

Industry Code	Industry Name
A	Agriculture, forestry, animal husbandry, fishery and auxiliary activities
B	Mining
C	Manufacturing
D	Electricity, heat, gas and water production and supply
E	Construction industry
F	Wholesale and retail industry
G	Transportation, warehousing and postal services
H	Accommodation and Catering Industry

I	Information transmission, Software and Information Technology Services
J	Financial Industry
K	Real Estate Industry
L	Leasing and business services industry
M	Scientific Research and Technical Services
N	Water, Environment and Utilities Management Industry
O	Resident services, repairs and other services
P	Education
Q	Culture, sports and entertainment industry
R	Culture, sports and entertainment industry

Note: This table follows the industrial classification for national economic activities issued by the China National Bureau of Statistics in 2017.

Table E2 The heterogeneous effect of city air connectivity on enterprise SO_2 emissions

	(1)	(2)	(3)	(4)	(5)	(6)
	Connecte d to more major cities	Connecte d to fewer major cities	Larger internatio nal flight ratio	Smaller internatio nal flight ratio	Larger destination internation al connectivit y	Smaller destinatio n internatio nal connectiv ity
Dependent variables	ln SO_2	ln SO_2	ln SO_2	ln SO_2	ln SO_2	ln SO_2
ln Air Connectivity	-2.089***	-0.099***	-1.235***	-0.090**	1.105	-0.098***
	(0.764)	(0.037)	(0.420)	(0.035)	(1.364)	(0.036)
ln age	0.068*	0.122***	0.105**	0.113***	0.092*	0.115***
	(0.038)	(0.021)	(0.051)	(0.020)	(0.049)	(0.020)
ln size	0.168***	0.138***	0.183***	0.143***	0.154***	0.150***
	(0.024)	(0.014)	(0.032)	(0.013)	(0.030)	(0.013)
ln capital intensity	0.058***	0.053***	0.047**	0.055***	0.042**	0.057***
	(0.014)	(0.008)	(0.021)	(0.007)	(0.017)	(0.008)
Foreign direct investment	-0.081	0.052	-0.056	0.023	-0.055	0.015
	(0.074)	(0.062)	(0.092)	(0.055)	(0.091)	(0.056)
State-owned enterprise	-0.182*	-0.022	-0.409***	-0.014	-0.360***	-0.013
	(0.106)	(0.068)	(0.136)	(0.062)	(0.121)	(0.064)
ln GDP	-1.181	0.699*	-1.628	0.202	-9.785***	0.280
	(1.606)	(0.367)	(2.452)	(0.238)	(3.301)	(0.328)
ln GDP per capita	0.868	-0.638*	1.369	-0.117	11.418***	-0.229
	(1.760)	(0.373)	(2.482)	(0.263)	(3.849)	(0.336)
Road density	-3.396***	-0.021	0.908	-0.113	-7.444***	-0.090
	(0.561)	(0.167)	(0.870)	(0.153)	(1.704)	(0.153)
HSR	0.041	0.007	-0.182	-0.006	0.043	0.004
	(0.085)	(0.045)	(0.114)	(0.037)	(0.171)	(0.041)
ln Education	0.874**	-0.089	-0.117	-0.061	1.749***	-0.073
	(0.379)	(0.076)	(0.412)	(0.075)	(0.414)	(0.076)

Environmental regulation	-10.971	-1.143	21.815	-6.182	-43.580**	-0.395
	(10.649)	(7.277)	(13.889)	(6.448)	(17.829)	(6.703)
Observations	69,619	185,467	44,399	210,695	42,471	212,622
Firm fixed effects	Y	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
K-P rk LM statistic	27.95	126.9	9.484	137.2	14.01	134.6
K-P rk Wald F statistic	23.14	501.3	16.68	581.3	26.33	502.8
Hansen J statistic (p value)	0.0222	0.0469	0.753	0.00668	0.0306	0.0409

Note: This table presents the 2SLS estimated impacts of city air connectivity on firm SO_2 emissions. The instruments are defined in equations 4.3 and 4.4. The subsamples are generated as follows: (1) considering the number of major cities the origin city is connected to; (2) the international flight ratio of the origin city; (3) the international connectivity of destinations of the origin city. Robust standard errors are shown in parentheses and clustered at the city-year level. *** p<0.01, ** p<0.05, * p<0.1.

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