THREE ESSAYS ON THE HETEROGENEOUS IMPACT OF HIGH-SPEED RAIL ON AVIATION

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Three Essays on the Heterogeneous Impact of High-Speed Rail on Aviation

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CERTIFICATE OF ORIGINALITY

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Abstract

The rapid expansion of high-speed rail (HSR) networks has fundamentally transformed intercity transportation systems, particularly in China, which operates 68% of the world's HSR infrastructure till 2023. This thesis examines the multifaceted interactions between HSR and air transport through three interconnected studies, addressing critical gaps in understanding their competitive dynamics, strategic adaptations, and systemic impacts.

First, we investigate how airfare adjustments channel HSR's impact on air traffic, decomposing price-relevant and price-irrelevant effects across heterogeneous markets. Our analysis reveals that airlines' fare responses significantly influence net traffic outcomes, with medium-quality HSR routes experiencing air traffic growth through fare reductions, while high-quality HSR routes see declines due to airfare increases. These findings highlight the crucial role of market-specific factors in shaping HSR-aviation competition.

Second, we analyze airlines' scheduling strategies in response to HSR competition, demonstrating heterogeneous response patterns that vary by route characteristics. On long-haul and slot-controlled routes, airlines increase departure-time differentiation, whereas short-haul routes exhibit flight clustering. This study reveals an important asymmetry in strategic flexibility, with severely affected markets showing limited differentiation options compared to moderately competitive ones.

Third, we develop an innovative framework to assess HSR's effects on airport catchment areas and inter-airport competition, incorporating door-to-door travel times at the itinerary level. Our findings demonstrate significant heterogeneity, with ma-

jor hub airports benefiting from catchment expansion while smaller regional airports experience contraction. Additionally, we observe a modest system-wide rise in competition intensity among airports. This uneven distribution of HSR's effects highlights the importance of coordinated infrastructure planning to ensure balanced regional accessibility.

Collectively, these studies advance empirical understanding of HSR-aviation interactions, provide evidence of constrained airline strategic scheduling responses, and develop innovative methodologies for airport accessibility analysis. The findings offer valuable guidance for policymakers and transportation planners, highlighting the need for integrated policies that balance HSR development with aviation sector sustainability. The research particularly emphasizes addressing emerging disparities between hub and regional airports, offering key insights for managing the complexities of multimodal transportation systems.

Publications Arising from the Thesis

1. Gu, H., Wan, Y., 2022. Airline reactions to high-speed rail entry: Rail quality and market structure. *Transportation Research Part A: Policy and Practice*, *165*, 511-532.

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Chapter 1

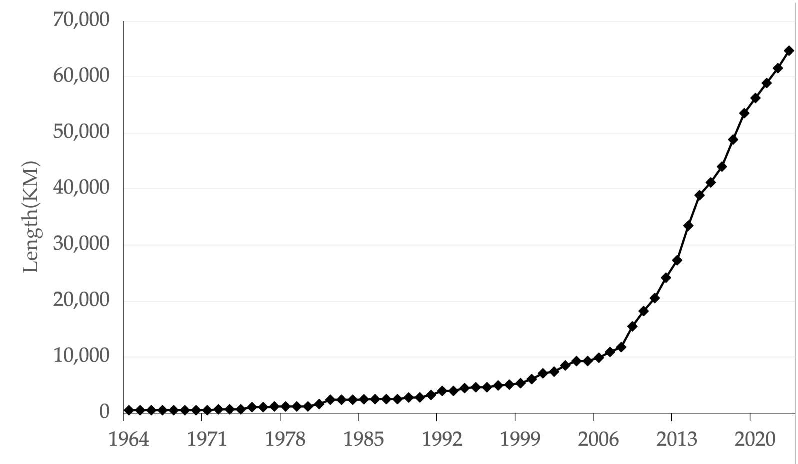
Introduction

The rapid development of high-speed rail (HSR) networks represents one of the most transformative advancements in modern transportation. Following China's inauguration of its first HSR line in 2008, the growth of HSR networks accelerated significantly. Between 2010 and 2019 – the year preceding the COVID-19 pandemic – global HSR passenger traffic increased by 3.4 times compared to 2010 levels. Notably, China accounted for 72.6% of global HSR traffic in 2019.[1] Figure 1.1 illustrates the global expansion of HSR infrastructure and traffic over time.

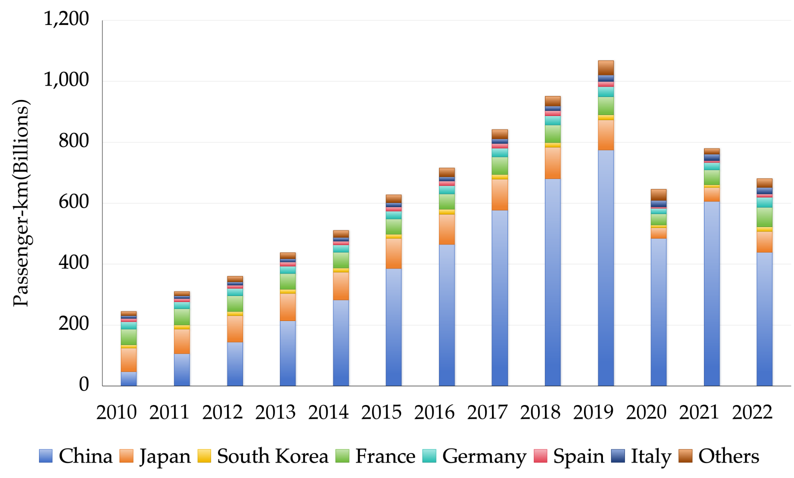
By 2024, China had established a preliminary eight-vertical-eight-horizontal HSR network, transporting 3.27 billion passengers annually. This figure represents 75.9% of total railway passenger traffic in the country. The network now connects 96% of Chinese cities with populations exceeding 500,000 (People's Daily, 2024).

These developments have sparked extensive discussions among policymakers, industry practitioners, and academics. They widely recognize HSR as a cleaner transportation mode compared to road transport and aviation for intercity travel. For instance, according to estimates by European Environment Agency (2014), HSR emits approximately 14 grams of CO2 per passenger-kilometer, whereas air transport emits 285 grams. Policymakers thus aim to replace short-haul flights with HSR connections to mitigate environmental harm. However, as noted by Givoni

[1] Data source: UIC High-Speed Database (Accessed 20 June 2025).



(a) HSR network length



(b) HSR network traffic

Figure 1.1: Worldwide HSR development

and Dobruszkes (2013) and Chen et al. (2021), HSR may also induce new travel demand, potentially offsetting its environmental benefits. Consequently, a thorough understanding of the interactions between HSR and aviation is essential to assess whether HSR can indeed contribute to environmentally sustainable transportation. A special emphasis should be placed on HSR's impact from the perspective of the entire network, rather than solely on parallel air routes, as most studies do. This broader view is necessary because HSR's network-wide effects – including potential complementarity with aviation – may also influence non-parallel routes.

Beyond environmental considerations, HSR also influences the post-pandemic recovery of air transport. Although the International Air Transport Association (IATA) declared in June 2024 the aviation industry had "fully recovered" from the COVID-19 pandemic (Aviation Business News, 2024), China's major airlines continue to report significant losses. Industry analysts attribute these losses partly to competition from HSR (Reuters, 2024). Consequently, understanding how airlines can identify opportunities in this competitive landscape has become a pressing concern for the aviation sector. This underscores the importance of examining the interactions between HSR and air transport, particularly their complementary effects and potential for intermodal integration.

This thesis synthesizes three interconnected studies examining the multifaceted interactions between HSR and air transport, contributing to a holistic understanding of the competition, cooperation, and strategic adjustments between these two modes of transport. Specifically, we address the following research questions:

1. What factors explain airlines' heterogeneous responses to HSR entry in terms of traffic volume and pricing strategies?
2. How do airlines adjust their scheduling operations in response to HSR competition?
3. To what extent does HSR expand airport catchment areas, and how does this affect competition among airports?

The first study seeks to reconcile contradictory findings in the literature regarding HSR's effects on air traffic volumes. We decompose its impact into two possibly opposing channels: (1) price-irrelevant effects (e.g., modal substitution) and (2) price-relevant effects (e.g., airline fare adjustments). Using fixed-effects panel data regressions across heterogeneous markets, we demonstrate that airfare responses play a pivotal role in determining the net impact of HSR on air traffic. Meanwhile, this effect exhibits significant variation depending on HSR service quality, pre-existing airline market structure, and potential for HSR-airline intermodal connectivity. These findings underscore the importance of considering market-specific factors and airfare regulations when evaluating the broader implications of HSR entry.

While the first study focuses on air traffic and pricing, the second study delves into airline scheduling strategies in response to HSR competition, a topic that has received little attention from researchers. We employ a fixed-effect regression model to analyze how HSR entry affects airline flight schedules, with a focus on differentiation strategies. The findings reveal heterogeneous impacts of HSR on airline scheduling strategies. On long-haul and slot-controlled routes, airlines tend to increase departure-time differentiation, moving farther away from competitors to maintain profitability in the face of reduced demand. In contrast, on short-haul and non-slot-controlled routes, within-airline differentiation decreases as airlines cluster flights around peak travel times to maximize load factors and reduce operational risks.

These results reveal a critical asymmetry in airlines' strategic flexibility: in markets severely affected by HSR, carriers face constrained options, often leading to intensified inter-airline competition with limited differentiation opportunities. In contrast, airlines confronting moderate HSR competition retain greater strategic latitude to adapt their scheduling practices.

The third study shifts the focus from airline strategies to the broader implications of HSR on airport catchment areas and inter-airport competition. Understanding an airport's catchment area – the geographical region from which it draws passengers – is crucial for evaluating its competitiveness, particularly in multi-airport regions (MARs) where passengers can choose from multiple airports. The expansion of HSR networks in China has redefined airport catchment areas by improving ground accessibility and creating new intermodal travel opportunities. However, this expansion has a dual effect: while it extends the market reach of certain airports, it also intensifies competition among airports, posing a negative competitive pressure.

The third study develops a novel framework for evaluating airport catchment areas based on detailed HSR and flight schedules, simulating door-to-door travel times from a passenger's perspective at the itinerary level. This approach captures not only the ground accessibility of each airport but also its direct connectivity and service quality, providing a more nuanced understanding of how HSR influences catchment areas. The findings reveal significant heterogeneity in HSR's impact on

China's airport system. Major airports with extensive flight networks and robust road-based feeding systems benefit from HSR connections as their catchment areas expand, while smaller airports with limited connectivity experience catchment area contraction.

Taken together, these three studies provide a comprehensive analysis of the interactions between HSR and aviation, addressing critical gaps in the literature and offering valuable insights for policymakers and industry stakeholders. First, policymakers should consider how airfare adjustments mediate HSR's impact on air traffic, as airlines' responses vary across markets due to differing market-specific factors. This is crucial when assessing the environmental effects of future HSR projects, since net air traffic changes depend on these conditions. Second, airlines could explore coordination with HSR operators to develop integrated intermodal services, mitigating the competitive pressures of HSR. Our findings reveal spontaneous passenger demand for intermodal travel (via separate ticket purchases), suggesting untapped complementarity between air and rail systems. Third, policymakers should prioritize integrated air-HSR network planning to ensure equitable airport connectivity development across regions.

The remainder of this thesis is organized as follows. Chapter 2 investigates how airfare adjustments channel HSR's impact on air traffic across heterogeneous markets. Chapter 3 examines airlines' strategic scheduling responses to HSR competition. Chapter 4 develops a novel framework to assess HSR's effects on airport catchment areas and competition. Finally, Chapter 5 concludes the thesis.

Chapter 2

Airline reactions to HSR entry: rail quality and market structure

2.1 Introduction

Till June 1st, 2021, the HSR lines in the world have reached 56,129 km, with 74,348 km lines under construction or planning. The rapid development of HSR has drawn much attention from scientific society in recent years. One of the most popular topics is how the emergence and prevalence of HSR service affect airline operations, in terms of air traffic, flight frequencies, and airfares (see Zhang et al., 2019, for a comprehensive review). The literature finds it difficult to reach an agreement on whether HSR threatens or benefits the aviation industry. While most research shows HSR's negative impacts on aviation (e.g., Jiménez and Betancor, 2012; Yang and Zhang, 2012; Albalate et al., 2015; Chen, 2017; Li et al., 2019b), some papers find HSR's positive impact on air traffic or seat capacity of certain routes (e.g., Wan et al., 2016; Zhang et al., 2018; Gu and Wan, 2020).

Airfare adjustment is one of the possible reasons for the contradictory findings on HSR's air traffic impact, which has never been formally studied empirically. Theoretically, a parallel entry of HSR service can impose two effects on air traffic, price-irrelevant effect and price-relevant effect. The price-irrelevant effect stems from passengers' preference shift, possibly due to vertical differentiation of the two modes. Passengers may be attracted by HSR advantages such as better on-time performance, more comfortable seating, and less station access/egress time, which are irrelevant to ticket price. The price-relevant effect indirectly affects air passenger number via airlines' response to adjust airfare upon facing the competition from HSR. For example, airlines might reduce airfare when facing a strong competitive pressure after HSR entry and the reduced airfare would attract more air passengers (Gu and Wan, 2020). The two types of effects on air traffic can act in opposite directions if airfare reduction takes place. Substantial airfare reduction might counteract HSR's traffic diversion effect and end up with a net increase in air traffic, although HSR is a competitive substitute of air transport.

The abovementioned price-relevant effect could vary significantly across markets, as various market forces affect airlines' strategy to adjust price upon entry of HSR. First, HSR quality, such as travel time, affects the attractiveness of HSR service relative to airline flights, and hence can influence airline's price reaction. Second, airline market structure is another potential source of diverse airfare adjustment upon the entry of HSR. In microeconomic theory, price is set at marginal cost in perfectly competitive market. Hence, in highly competitive markets, airlines have little room for further price cut after HSR, a new competitor, enters the market. In contrast, in the market where airlines possess strong market power (i.e., low competition level), the markup could be high (Collins and Preston, 1969), making airfare reduction more feasible post HSR entry.

In addition to the impacts imposed by the entry of overlapping HSR services, HSR can affect air traffic by providing additional ground connections to air transport and form air-HSR intermodal transport. As a result, extra air travel demand can be generated (Vespermann and Wald, 2011; Gu and Wan, 2020). This is termed as feeding effect of HSR in the literature. While the feeding effect can directly increase air passenger number and serve as another force that counteracts with the traffic diversion effect of HSR, theoretically, HSR's feeding expands airlines' catchment and thus may put upward pressure on airfare (Gu and Wan, 2020), which would again indirectly affect air traffic in the direction opposite to the direct effect of HSR feeding. In other words, HSR feeding would also have price-relevant and price-irrelevant impacts on air traffic.

It is not surprising that varying empirical results are found in literature as existing studies overlook the potentially varying price-relevant effects and almost all of them ignore the HSR feeding effects. Therefore, we attempt to contribute to the literature with a richer and deeper understanding on airlines' reactions to HSR entry by quantifying the amount of air traffic impacts which is channeled indirectly by airfare adjustment and decomposing several sources of heterogeneity that contribute to the variation in price-relevant effects as well as net air traffic impacts. Besides, decomposing the price-relevant and price-irrelevant effects has very important policy implications. Applying empirical findings from markets with strong price-relevant effects to a market where airlines have limited ability to adjust price would lead to wrong decision making even when the other factors associated with the attractiveness of these two transportation modes are the same. In addition, a better understanding on the price-relevant effect would help policy makers to provide a sound adjustment on competition and price-related regulation, which may be indispensable for realizing the desired outcomes of HSR entry. As far as we know, none of the existing studies has highlighted the importance of jointly considering airfare regulation and the entry of HSR.

Combining the research gaps identified above, this chapter aims to investigate (1) to what extent post-entry air traffic change is channeled by airfare adjustment, (2) how HSR qualities and pre-entry airline market structure associates with airfare adjustment, which in turn leads to heterogeneous net impacts on air traffic, and (3) whether feeding effect influences airfare and is also channeled by airfare adjustment. To identify whether airfare adjustment affects traffic, coefficients from two traffic regression models are compared. One model includes airfare as the independent variable, while the other one does not. HSR quality is measured by HSR-air travel time difference (TTD), and feeding effect is captured by the number of HSR feeding cities. They are employed in the regression to quantify heterogeneous reactions of air traffic. HSR-related components are then included in the airfare regression to capture the heterogeneity in airfare reactions. The role of pre-entry market structure is examined by estimating the above models with subsamples that have different competition levels pre-entry.

The models are estimated with a panel dataset that contains monthly air traffic and fare information for routes between the twenty busiest airports in China during 2012-2015. We find that price adjustment plays a significant role in air traffic change after the entry of HSR. For example, on routes with medium level of HSR quality (TTD between 5 and 9 hours), although HSR's parallel entry has little price-irrelevant impact on air traffic, the price-relevant effect eventually leads to a net increase in air traffic because airfares of these routes are found to decline after HSR entry. On routes with very high HSR quality or high level of pre-entry competition, in addition to the negative price-irrelevant effect of HSR on air traffic, the price-relevant effect is found further pushing the air traffic downward as airfare increases in these markets. HSR's feeding ability is found to substantially increase air traffic and meanwhile increase the airfare. Combining all the effects, we find HSR introduced over 16.5 million additional passengers to the sampled air routes in our study period, accounting for 6% of the four-year total air traffic of the sample routes and generating 2.17 million tons of extra CO2 emissions from air flights. However, these numbers would increase to 32.2 million additional passengers (11.7% of the total air traffic of the sampling period) and 3.4 million tons of extra CO2 emissions after excluding price-relevant effects.

The rest of the chapter is organized as follows. Section 2.2 reviews the literature. Section 2.3 provides description of the sample and data. Section 2.4 describes the empirical models and variables. Section 2.5 presents the regression results and section 2.6 provides policy discussion and estimates changes in airline CO2 emissions due to the entry of HSR to our sample routes. Section 2.7 concludes the chapter.

2.2 Literature review

Airlines' reactions to HSR competition have been intensively investigated, especially in the scope of airfare, air traffic, flight frequencies, and seat capacity. However, the literature present mixed results regarding HSR's impacts on airline market. A large group of empirical studies confirm HSR's downward pressure on air traffic, in terms of air passenger volume, seat capacity, flight frequency and market share (e.g., Park and Ha, 2006; Jiménez and Betancor, 2012; Albalate et al., 2015; Chen, 2017; Li et al., 2019a,b) and on airfare (e.g., Capozza, 2016; Wei et al., 2017; Wang et al., 2018). However, some studies reveal that such negative pressure can vanish and is even reversed on some specific markets. Wan et al. (2016) apply the difference-in-differences approach and find although HSR entry leads to, on average, a significant drop in airline seat capacity in China, HSR induces more air capacity on long-haul routes. Comparatively, there is no obvious impact of HSR in Japan on long-haul air markets. Using different samples, Zhang et al. (2018) and Gu and Wan (2020) also find HSR services in China encourage long-distance air travel. According to Gu and Wan (2020)'s theoretical prediction with a differentiated price competition model, substantial price adjustment post entry of HSR might explain the mixed empirical findings.

Although airline price is incorporated in many theoretical models of air-HSR competition as a decision variable which in turn affects equilibrium traffic (e.g., Yang and Zhang, 2012; Xia and Zhang, 2016; Gu and Wan, 2020), the empirical literature provides little discussion on how airlines' price response plays a role in the change in air traffic. Our review discovered two streams of empirical studies that investigate the impacts of HSR entry on air traffic. The first stream entirely excludes airfare from the model estimation. Most empirical studies fall into this category, and we listed a few representative studies in the upper panel of Table 2.1. The commonly used specification regresses air traffic or seat capacity on the presence of HSR service or/and HSR attributes plus other control variables of market characteristics. As airfare is not controlled in those studies, the results in fact reflect the net (or total) impact of price-relevant and price-irrelevant effects of HSR entry. Since the two effects can act in opposite directions, it is not a surprise to see mixed impacts on air traffic from the literature.

The second stream includes airfare as an independent variable, in addition to variables indicating HSR presence or/and attributes, in the model specification. As indicated in the lower panel of Table 2.1, we only find three studies in this stream. As airfare is controlled in these regression models, HSR-related variables in this case only capture the price-irrelevant effect on air traffic. Apart from the regression models that explicitly studies the impact of HSR entry, airline price has also been widely incorporated in discrete choice models to examine factors influencing travelers' modal choice and utility when air flights and HSR are among the alternatives (e.g., Martín and Nombela, 2007; Behrens and Pels, 2012; Li et al., 2020, to name a few). These studies model cases where HSR already operates in the market. Hence, they do not investigate the impact of HSR entry, and more importantly cannot quantify the price-relevant effect.

As the first stream fails to decompose price-relevant and price-irrelevant effects while the second stream only captures price-irrelevant effects, none of the studies in the literature can provide a clear insight on the role of airfare adjustment in air traffic impacts of HSR. To our knowledge, Yang et al. (2018) is the only group of researchers who are aware of the role of airfare in channeling HSR's impact on air travel demand. They first model individual air traveler's utility with a structural logit model including airfare as one determining factor. Then, they estimate the impact of HSR on airfare and flight frequency and demonstrate how HSR-induced airfare change affects individual air passenger's utility. However, as HSR-related variables are excluded from the utility model, their study only covers HSR's indirect effect on air passengers' utility via affecting airfare and flight frequency whilst the direct impacts are not captured. Besides, the impacts on air traffic are not explicitly quantified in Yang et al.'s study, because the focus is the utility of individual air passenger.

Table 2.1: Empirical studies and methodology on airline reactions to HSR entry

Paper	Sample	Method	Main variables	Main results
Airfare not as independent variable. Quantifying the net (total) impact				
Albalate et al. (2015)	Domestic trips in France, Germany, Italy and Spain	Linear regression model	DV: airline seat capacity, flight frequency; IV: HSR dummy	HSR entry has a ***negative*** effect on airline seat capacity, not flight frequency.
Castillo-Manzano et al. (2015)	Domestic trips in Spain	Dynamic linear regression model	DV: air traffic; IV: number of HSR passengers	HSR entry has a ***negative*** effect on air traffic.
Chen (2017)	Domestic trips in China	Linear regression model	DV: air traffic, flight frequency, airline seat capacity; IV: HSR dummy	HSR entry has ***negative*** effects on air traffic, flight frequency and seat capacity.
Jiménez and Betancor (2012)	Domestic trips in Spain	2SLS regression model	DV: airline market share, flight frequency; IV: HSR dummy, HSR passengers	HSR entry has ***negative*** effects on the flight frequency and airline market share.
Li et al. (2019b)	Domestic trips in China	DID linear regression model with unbalanced panel data	DV: air traffic per airport; IV: HSR dummy, HSR frequency, number of rail passengers	HSR entry has a ***negative*** effect on air traffic.
Wan et al. (2016)	Domestic trips in China, Japan and South Korea	DID linear regression model with propensity score matching approach	DV: airline seat capacity; IV: HSR dummy	HSR entry has a ***negative*** effect on airline seat capacity on short- and median-haul routes, but a ***positive*** effect on long-haul routes in China and no significant effect on long-haul routes in Japan.
Zhang et al. (2018)	Domestic trips in Mainland China, Japan, South Korea and Taiwan	DID linear regression model with propensity score matching approach	DV: air traffic per route, air traffic per airport; IV: HSR dummy	HSR entry has a ***negative*** impact on air traffic on short- and medium-haul air routes, and a ***positive*** effect on long-haul air travels.
Airfare as independent variable. Quantifying price-irrelevant effect				
Li et al. (2019a)	Domestic trips in China	DID linear regression model with panel data	DV: air traffic; IV: HSR dummy, HSR frequency, airfare	HSR entry has a ***negative*** impact on air traffic.

Table 2.1 continued from previous page

Paper	Sample	Method	Main variables	Main results
Yang et al. (2018)	Domestic trips in China	Linear regression model with panel data and hybrid random effects model with unbalanced panel data	DV: air traffic; IV: HSR dummy, HSR frequency, HSR travel time, HSR fare, airfare	HSR entry has a ***negative*** effect on air traffic.
Zhang et al. (2017)	Domestic trips in China	Linear regression model with panel data	DV: air traffic; IV: HSR dummy, airline yield	HSR entry has a ***negative*** effect on air traffic.

Notes: DV = dependent variables; IV = independent variables of interest. Other control variables are omitted in the table to save space.

In addition to revealing the fact that airfare's channeling role has been largely ignored in the previous studies, our literature review also suggests two issues may complicate the airlines' response in airfare and in turn the impacts on post-entry air traffic and as a result should be incorporated into our study. First, airline market structure may affect airfare in the context of air-HSR competition. Wang et al. (2018) show with an analytical model that inter-airline competition can moderate the effect of raising HSR speed on airline price. Empirically, we only find one indirect evidence showing that HSR effect on airfare is more prominent in thin market than thick market (Zhang et al., 2017). However, this implicit finding is based on analysis of some descriptive statistics instead of a formal statistical investigation. Moreover, whether market structure is statistically different in thin and thick market in China is yet to be verified, although some researchers have shown that market structure varies significantly in thick and thin airline markets (Graham et al., 1983; Bhadra and Kee, 2008). Second, HSR quality in terms of travel time and operation speed can affect airfare. Although shorter HSR travel time (or higher HSR speed) has been widely found associated with less air travel demand (e.g., Gonzales-Savignat, 2004; Behrens and Pels, 2012; Dobruszkes et al., 2014; Wang et al., 2018), its impact on airfare is only discussed in a few papers. Yang and Zhang (2012) show with a theoretical model that airlines will respond with a larger price cut if the competing HSR service operates at a higher speed. This prediction is verified in several empirical studies. Capozza (2016) finds airlines set higher fares as rail travel time increases. Zhang et al. (2017) and Wang et al. (2018) demonstrate that HSR introduces a larger negative impact on airfare on short-haul routes, where HSR travel time is more comparable with air travel time.

2.3 Sample and data

The unit of the analysis is year-month-city pair observations, with both directions of city pairs aggregated.[1] Our sample includes city pairs that connect the top twenty

[1]Both non-stop flights and direct flights with stops are considered.

airports in China in terms of air passenger traffic to reduce the unexpected effects of irregular operations in weak markets. The list of airports and cities can be found in Appendix A.1. City-pair routes with unstable air service provision are deleted from the sample to obtain a balanced panel dataset. In such a way, routes kept in the dataset had air service for the whole study period. The routes with monthly passenger numbers below 100 are further removed from the dataset to exclude the possible outliers. After data filtering, our sample contains 155 domestic routes and each route is observed for 48 months from January 2012 to December 2015, resulting in a total of 7,440 observations.

As China's first HSR service was launched in 2008, 18 routes in the sample already had HSR service from the beginning of the study period. However, since China's HSR network was rapidly expanding from 2012 to 2015, HSR entered a fair number of sampled routes during the study period. The distribution of sampled air routes in months of HSR service by the end of the study period is summarized in Table 2.2. If HSR entered a route market in the first half of a month, the route's observations of this month and all the following months are considered to have HSR presence. If HSR entered in the second half of a month, the entry is considered to start in the following month. In total, 78 routes did not have HSR service throughout the study period, while new HSR service started on 59 routes during the study period. The sampled routes represent a fair variation of HSR service duration.

Table 2.2: HSR service duration and number of routes

	Months of HSR operation *	No. of routes
No HSR presence	0	78
HSR opened between 2012-2015	1-10	6
	11-20	19
	21-30	19
	31-47	15
HSR opened before 2012	48	18
	Total	155

Notes: * The first month of operation is included.

Two datasets are used to obtain relevant airline passenger transport data of a city pair. Air traffic data is drawn from the IATA Airport Intelligence Services database.

The dataset contains monthly aggregated ticket information of Chinese domestic routes from January 2012 to December 2015, including monthly passenger number and average airfare charged by each airline. The second source, OAG Schedule Analyzer, includes detailed flight schedules of all airlines that operate on certain routes, such as scheduled departure and arrival time, number of seats provided and planned flying time of each flight. The scheduled flight time (air travel time hereafter) of each route and seat capacity of an average flight is calculated based on OAG Schedule Analyzer. Due diligence of the two sources is undertaken to ensure the consistency and reliability of the data.

Information and data associated with HSR services are collected and derived from the National Rail Timetable of China (July edition, 2012–2015). In addition to train services with a maximum speed reaching 350 km/h, this study also includes trains with a maximum speed reaching 200-250 km/h. Although the latter type of service is not called "high-speed rail" in China, its operation speed is far above the conventional trains of which the maximum speed is 160 km/h and hence its entry should have impacts on airlines. The timetable contains detailed information on rail operation plan, including departure and arrival time at each stop served by each train. As some HSR services started before the release of the July-edition Timetable, the exact entry month of each HSR service is obtained from the news released by local governments and official media so as to fit in the monthly-level analysis. Similar to how we deal with multiple airports in a city, multiple HSR stations in the same city are also aggregated to the prefectural-city level.[2]

2.3.1 Air-rail travel time difference and pre-entry market structure

To better understand heterogeneous airline reactions, the air-rail quality difference and pre-entry airline market structure are two dimensions of consideration in this chapter. As highlighted by Gu and Wan (2020), due to the variations of railway

[2]Intra-city rail services are excluded from the analysis since our focus is on airline reactions in inter-city market.

distances, operation speed and stops between the origin and destination cities, rail travel time can vary significantly among routes with similar air distances. Thus, to investigate heterogeneous airline reactions, instead of considering different air route distances, we use the scheduled in-vehicle time (hereafter, travel time) difference of the two modes (HSR travel time minus air travel time) to capture the relative quality difference. For city-pair routes served by different HSR services with varying in-vehicle times, the rail travel time is measured by a frequency-weighted average value across different train services. For the routes that have both non-stop and stop-over flights, the scheduled flying time of non-stop flights is used to approximate passengers' perceived travel time.[3] Based on travel time differences (TTD) between HSR and air, routes are categorized into six groups, namely routes with rail-air TTD below 3 hours, between 3 and 5 hours, between 5 and 7 hours, between 7 and 9 hours, above 9 hours and routes without HSR service presence. Note that the larger the TTD, the less attractive (lower quality) the HSR service, the more attractive (higher quality) the air service, ceteris paribus. As shown by Gu and Wan (2020), although longer air routes tend to have higher rail-air TTD as air transport has more advantage in long-haul markets, it is commonly observed that some long-haul (over 1000 km) air routes have very low TTD and some short-haul (below 500 km) air routes have very high TTD.

Note that as operation speed and number of stops of HSR services of a city pair can change over time, so can rail travel time. As a result, one route may fall into different TTD groups in different years. For example, the Zhengzhou-Chongqing route experienced a 110-minute reduction of travel time in 2015, making the route switch from the group with TTD between 7 and 9 hours to the group with TTD between 5 and 7 hours. Table 2.3 shows the route distribution of TTD groups by year. In the earlier years of our study period, there are no observations in the group of TTD above 9 hours, as very long-haul HSR services did not appear until

[3] It would be better to treat non-stop and direct flights with stops differently, since their flying times could differ a lot. However, due to limited traffic data, we cannot distinguish passenger numbers of non-stop flights and stop-over flights. Together with the fact that the proportion of stop-over flights is relatively low (12.4% on average), we take the scheduled flying time of non-stop flights as the air travel time.

individual railway segments are constructed and linked with each other to form a larger network. In 2015, with fast expansion of HSR network, more than half of the observations have HSR operation. In general, most routes have TTD between 3 and 7 hours.

Table 2.3: Number of route-month observations by TTD and year

TTD	<3 hrs	3-5 hrs	5-7 hrs	7-9 hrs	>9 hrs	No HSR	Total
2012	54	102	73	36	0	1,595	1,860
2013	60	192	150	30	0	1,428	1,860
2014	72	216	213	119	84	1,156	1,860
2015	80	252	216	194	154	964	1,860
Total	266	762	652	379	238	5,143	7,440

Airline market structure is captured by the route-level Herfindahl-Hirschman Index (HHI) based on the seat capacity shares of individual airlines operating in the same route market before the entry of HSR.[4] In calculating seat capacity shares, airlines under the same parent company are treated as one firm and their seat capacity is added up together.[5] Since we aim to examine how the pre-entry market structure affects airline responses, we first exclude the routes that already have HSR service at the beginning of the study period. Then we create two subsamples according to HHI values before HSR entry, specifically HHI in January 2012, i.e., the first period of our sample. Routes with HHI below 0.3 are considered as the high competition subsample while routes with HHI above 0.3 are considered as the low competition subsample. The distribution of routes by TTD and market structure is shown in Table 2.4. The threshold 0.3 ensures a similar number of observations between subsamples in most TTD groups, which is beneficial for further comparison of the two subsamples.

[4]The reason for not using traffic to calculate HHI is that traffic data we obtained do not include passengers who book tickets directly from the airline (instead of from agents). If different airlines have different proportions of agent-passengers, HHI calculated by traffic data could be misleading and biased. Note that we use HHI before the entry of HSR to measure market structure because some airlines may exit the market after the introduction of HSR, leading to an increase in airline concentration post entry (Qin et al., 2024).

[5]The ownership of all the sample airlines is listed in Appendix A.2.

Table 2.4: Number of route-month observations by TTD and pre-entry market structure

TTD	<3 hrs	3-5 hrs	5-7 hrs	7-9 hrs	>9 hrs	No HSR	Total
Pre-entry competition level							
High	33	153	173	158	72	2,003	2,592
Low	53	201	239	185	166	3,140	3,984
Total	86	354	412	343	238	5,143	6,576

Notes: The table does not include the routes that have HSR presence at the beginning of the study period. Thus, the total observation number is different from the full sample size 7,440.

2.3.2 HSR feeding cities of air routes

Another feature of HSR development in China is that HSR serves many small cities that have no airports. When such small cities are linked to the airport cities by HSR, it is more convenient for passengers to take flights at the airports that are relatively far from their origins. Thus, HSR can expand the catchment area of airports (Vespermann and Wald, 2011). Following the spirit of Gu and Wan (2020), we measure HSR's potential to feed air flights with the number of HSR feeding cities of each air route. The distinction of our measure is that the transfer possibility is considered by matching air flight and HSR schedules. We assume that air-HSR connection is feasible only when the connection time is within a certain range. A connection will likely be missed if the connection time is too short, while the prolonged total trip time will make air-HSR connection unattractive if the connection time is too long. Considering that in most of the sample cities, HSR stations are far from the airport, the feasible connection window is assumed to be between three and five hours. That is, the time interval between arrival of the first leg and departure of the second leg should be between three and five hours. Thus, a city will be considered as a feeding city of a focal air route when the following conditions are satisfied: (1) The city has no direct flights to reach any endpoint city of the focal route but has HSR services to at least one endpoint city of the route, and (2) at the endpoint city with HSR service, the air-HSR connection time is within the feasible connection window.[6]

Figure 2.1 illustrates a basic example of feeding city. Node F stands for a feeding city of the focal route AB. Passengers travelling between city F and city B need to

[6]Note that the city is regarded as feeding city if there is at least one HSR-air schedule combination that satisfies the feasible connection window.

transfer at city A. Note that the air route AB is assumed to have feeding cities no matter it has parallel HSR service or not. If cities A and B are also connected by HSR, which is not shown in the figure, passengers might choose HSR for both FA leg and AB leg of the trip. This would introduce air-HSR competition on the AB leg and such competition effect can be captured by other variables in the empirical model.

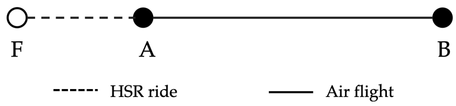


Figure 2.1: Illustration of the feeding city

Table 2.5 shows the average number of feeding cities on routes with HSR service or without HSR service during our sample period. HSR routes refer to air routes that have HSR entry any time by the end of the study period. Some HSR routes started HSR operation in the middle of the study period, so these routes have no HSR presence in certain earlier years. Non-HSR routes refer to air routes without HSR service throughout the study period. HSR routes, with or without HSR presence, have more feeding cities than non-HSR routes. On average, HSR routes have almost twice the number of feeding cities of non-HSR routes. As the HSR network expands, the average number of feeding cities of all routes has more than doubled during the four years. The number rises most rapidly in 2015.

Table 2.5: Average number of feeding cities by route type and year

	HSR routes			Non-HSR routes	Pooled
Year	HSR presence	No HSR presence	Pooled		
2012	46	39	41	19	30
2013	64	54	59	32	45
2014	62	54	60	34	47
2015	99	80	98	58	78

2.4 Empirical models and variables

We model airlines' reactions to HSR's parallel entry as well as HSR feeding services in air traffic and airfares. The aim is to examine whether and to what extent the air traffic impact is channeled by the adjustment in airfares as well as the role of HSR quality and pre-entry market structure in heterogeneous airline reactions. The main models are specified as follows:

$$\begin{aligned} Pax_{it} = \alpha_0 + &\sum_{m=1}^{5} \alpha_m Dm_{it} + \alpha_6 Fare_{it} + \alpha_7 Feeding_{it} \\ &+ \alpha_8 HSRmonth_{it} + \alpha_9 LCCshare_{it} + \alpha_{10} RouteGDP_{it} \\ &+ \alpha_{11} RoutePop_{it} + route_i + year_t + month_t + \varepsilon_{it} \end{aligned} \tag{2.1}$$

$$\begin{aligned} Pax_{it} = \beta_0 + &\sum_{m=1}^{5} \beta_m Dm_{it} + \beta_6 Feeding_{it} + \beta_7 HSRmonth_{it} \\ &+ \beta_8 LCCshare_{it} + \beta_9 RouteGDP_{it} + \beta_{10} RoutePop_{it} \\ &+ route_i + year_t + month_t + \epsilon_{it} \end{aligned} \tag{2.2}$$

$$\begin{aligned} Fare_{it} = \gamma_0 + &\sum_{m=1}^{5} \gamma_m Dm_{it} + \gamma_6 Feeding_{it} + \gamma_7 HSRmonth_{it} \\ &+ \gamma_8 LCCshare_{it} + \gamma_9 HHI_{it} + route_i + year_t + month_t \\ &+ \mu_{it} \end{aligned} \tag{2.3}$$

The key variables of interest are those describing HSR characteristics, including HSR quality (Dm_{it}), HSR feeding capability ($Feeding_{it}$), and time elapse after HSR entry ($HSRmonth_{it}$). A set of dummy variables Dm_{it} ($m = 1, \ldots, 5$) is used to capture HSR's heterogeneous impacts on parallel air routes attributed to different HSR qualities measured by TTD. Following the six categories defined in Section 2.3.1, five dummies are constructed accordingly, i.e. $D1$, $D2$, …, $D5$, representing routes with rail-air TTD below 3 hours, between 3 and 5 hours, between 5 and 7 hours, between 7 and 9 hours, above 9 hours, respectively. The base case is in fact the sixth category, representing observations that had no HSR presence, including routes that never had HSR service in the study period and pre-entry periods of routes that encountered HSR entry in the middle of the study period. The five categories of routes with HSR presence are compared separately with the base case to capture the heterogeneity of HSR effects in terms of HSR quality relative to air flights (or relative attractiveness/advantages of the two modes). For example, α_1 represents HSR's impact on air routes with the highest HSR quality, while α_5 measures HSR's impact on the air routes with the lowest HSR quality. Note that an interaction of HSR dummy and a continuous TTD variable cannot capture the same feature, because cases without HSR presence and those with HSR service but zero TTD (when HSR service has the same travel time as the air flights) have the same interaction value. Thus, one single interaction term fails to differentiate these two cases and hence we must construct several categories of TTD. $Feeding_{it}$ refers to the number of feeding cities for route i at time t, as defined in Section 2.3.2. It captures HSR's impact on air traffic by feeding passengers from cities without airports to air route i and hence we expect its coefficient to be positive. $HSRmonth_{it}$ denotes the number of months that HSR is in operation on route i till time t. This variable is used to capture the potential time-lagged effect of HSR operation. Passengers as well as airlines may gradually get used to the entry of HSR over time, thus making HSR's impact vary over time. It can also be interpreted as the long-term impact. This long-term impact was also investigated by Yang et al. (2018) and Yang et al. (2020).

One may argue that HSR entry is endogenous. The market with stronger travel demand is more likely to attract HSR entry. In fact, HSR network development in China involves massive financial investment led by the national and local governments to facilitate mobility of not only well-developed regions but also less developed areas. In many less developed regions, HSR is considered as a local economic booster instead of merely a transportation mode. Thus, the decisions on which cities should be linked to the HSR network do not solely depend on the characteristics of travel demand but many other considerations, including technological convenience. Moreover, all cities above a certain population threshold are initially planned to be linked into the HSR system. As our sample only includes large cities, all non-HSR routes in our sample are likely to encounter HSR entry at a certain point of time in the future as the construction of planned HSR lines is gradually completed. Thus, the risk of potential selection bias is low in this study.

To study whether and how airfare plays a role in HSR's impact on air traffic, we specify two traffic equations. Eq.(2.1) models HSR's impact on air passenger traffic on route i in time t (Pax_{it}) after explicitly controlling for airfare adjustment. $Fare_{it}$ refers to airfare and its coefficient reflects air passengers' sensitivity to airfare. We employ HHI_{it} constructed based on seat capacity shares of all airlines operating on route i at time t as the instrumental variable to deal with the possible endogeneity issue between air traffic and airfare. Note that this HHI_{it} varies in time t, which is different from the HHI used to define pre-entry market structure mentioned in Section 2.3. As airfare is controlled in Eq.(2.1), dummy variables $D1_{it} \sim D5_{it}$ quantify an extra impact of HSR if airfare were unchanged post-entry. This impact can be explained by passengers' preference shift that has no relation to prices.[7] For example, air passengers on the routes with a high-quality HSR service (small HSR-air TTD) might shift to HSR service because of HSR's comfortable seating, better on-time performance or less access/egress time.

Eq.(2.2) is a variant of the main traffic model in the sense that it excludes variable $Fare_{it}$ while keeping everything else the same as in Eq.(2.1). As airfare is not controlled in Eq.(2.2), the HSR-related variables in this specification quantify the net traffic effect from two possible sources: (a) HSR-induced airfare adjustment and (b) preference shift irrelevant to airfare adjustment. By comparing coefficients of the dummy variables estimated by the two models, we can infer whether post-entry airfare adjustment serves as a crucial channel of air traffic changes. If price reduction takes place post-entry, it will pose an upward pressure on air traffic. Then, if this price adjustment channels the impact on air traffic, we expect the coefficients of the dummy variables will reduce after controlling for price. That is, $\alpha_m < \beta_m$. Note that if $\alpha_m < 0$, β_m can even be positive. In some social science fields, such as psychology and sociology, this kind of effect is termed as the mediation effect (Baron and Kenny, 1986). In applied econometrics, one may also interpret the difference in estimated coefficients between Eq.(2.1) and Eq.(2.2) as empirical evidence of the significant role of price response in determining the ultimate impact on air

[7]As China did not start market-based pricing for HSR services until 2016, there was little variation in HSR prices in the study period and the impact of HSR price variation is minimal.

traffic. This potential price-response effect has been largely ignored in the empirical literature of air-rail competition (e.g., Jiménez and Betancor, 2012; Albalate et al., 2015; Castillo-Manzano et al., 2015; Wan et al., 2016), though explicitly modeled in some theoretical papers (e.g., Yang and Zhang, 2012; Xia and Zhang, 2016).

Eq.(2.3) specifies the impact of HSR entry on airfare. We assume all the HSR-related features can have an impact on airfare, including HSR quality, feeding effect, and time lag effect. After estimating both Eq.(2.2) and Eq.(2.3), the so-called "mediation effect" in some social science fields can be quantified as $\gamma_m \times \alpha_6$ (Baron and Kenny, 1986).

Eq.(2.1), (2.2) and (2.3) are first estimated with the full sample to examine the role of airfare in affecting air traffic post-entry and heterogeneous airline responses related to HSR quality. The three specifications are then estimated with the two subsamples with different pre-entry competition levels. Comparisons of the coefficients from these two subsamples would reveal whether airline reactions vary in pre-entry airline market structure.

Several additional variables affecting airline traffic and price are controlled. $LCCshare_{it}$ captures the impact of market share of low-cost carriers on the route average price and traffic. The sum of GDP per capita of the two endpoint cities of the focal route and the total population are considered in the traffic equation to control for market demand. The fare equation includes HHI to control for the impact of competition level on route-level average airfare. Three-way fixed effects – route, year and month fixed effects – are included to control for unobservable attributes of a specific route, year or month. The notations and definitions of all variables employed in the empirical models are listed in Table 2.6. Summary statistics of main variables are listed in Table 2.7.

Table 2.6: Notations and definitions of variables in Eq.(2.1), (2.2) and (2.3)

Variable notation	Definition
Pax_{it}	Total air passenger traffic on route i in month t
$Fare_{it}$	Average airfare on route i in month t
$D1_{it}$	Dummy variable. It takes a value of 1 if HSR-air TTD is below 3 hours on route i in month t; otherwise, it takes a value of 0.
$D2_{it}$	Dummy variable. It takes a value of 1 if HSR-air TTD is between 3 and 5 hours on route i in month t; otherwise, it takes a value of 0.
$D3_{it}$	Dummy variable. It takes a value of 1 if HSR-air TTD is between 5 and 7 hours on route i in month t; otherwise, it takes a value of 0.
$D4_{it}$	Dummy variable. It takes a value of 1 if HSR-air TTD is between 7 and 9 hours on route i in month t; otherwise, it takes a value of 0.
$D5_{it}$	Dummy variable. It takes a value of 1 if HSR-air TTD is above 9 hours on route i in month t; otherwise, it takes a value of 0.
$HSRmonth_{it}$	Number of months the HSR service is operated on route i till month t
$Feeding_{it}$	Number of HSR feeding cities of route i in month t
HHI_{it}	Herfindahl–Hirschman Index of route i in month t in terms of seat capacity
$LCCshare_{it}$	Traffic share of low-cost carriers on route i in month t
$RoutePop_{it}$	Total population of the two endpoint cities of route i in month t
$RouteGDP_{it}$	The sum of GDP per capita of the two endpoint cities of route i in month t

2.5 Results

2.5.1 Airline reactions to parallel HSR entry: heterogeneous HSR quality

Table 2.8 presents the regression results using the full sample. The first column refers to panel data two-stage least square (2SLS) estimation results of the full traffic model Eq.(2.1) which controls for airfare and uses HHI_{it} as the instrumental variable of airfare. As expected, airfare has a negative impact on air passenger traffic. After controlling for airfare, HSR still has a significant effect on air traffic, especially on routes where HSR quality is high relative to air transport in terms of travel time (TTD $<$ 5 hours), and on routes where HSR quality is the lowest (TTD $>$ 9 hours). In particular, HSR has the largest negative impact on air traffic on routes with TTD less than 3 hours, which almost doubles the negative impact on

Table 2.7: Descriptive statistics of variables

Variables	N	Mean	SD	Min	Max	Unit/Note
Pax	7,440	35,311	35,475	1,450	282,775	
Fare	7,440	129.6	40.79	43.63	310.5	USD
HSRmonth[a]	7,440	10.77	22.63	0	96	
Feeding	7,440	50.08	29.83	0	133	
Airtime[b]	7,440	132.3	41.93	50.67	255.2	Minute
HSRtime[b]	2,297	458.1	169.9	165.9	908	Minute
TTD[b]	2,297	5.750	2.533	1.498	12.56	Hour
D1	7,440	0.0358	0.186	0	1	Dummy
D2	7,440	0.102	0.303	0	1	Dummy
D3	7,440	0.0876	0.283	0	1	Dummy
D4	7,440	0.0509	0.220	0	1	Dummy
D5	7,440	0.0320	0.176	0	1	Dummy
HHI	7,440	0.368	0.140	0.147	1	
LCCshare	7,440	0.0436	0.0856	0	0.811	
RouteGDP	7,440	171,774	39,156	79,744	282,482	000
RoutePop	7,440	21,804	9,697	4,392	54,318	000

Notes: [a] The maximum number of HSR months (i.e. 96) exceeds our sample size (i.e. 48), because some routes started HSR operation a few years before 2012. [b] Airtime represents in-vehicle travel time of air flights. HSRtime represents in-vehicle travel time of HSR service. TTD represents HSR travel time minus air travel time. These three variables are not directly utilized in the model, but they are crucial in determining the route categories.

routes with TTD around 3-5 hours (from a reduction of 13,848 air passengers to a reduction of 6,876 air passengers on average according to the coefficients of $D1$ and $D2$ presented in Eq.(2.1) of Table 2.8). As mentioned above, this could be explained by passengers' preference shift away from aviation when there is no change in airfare. However, on routes with TTD above 9 hours, the positive coefficient indicates that airlines gain extra traffic after HSR entry. In sum, if airlines do not react to parallel HSR entry by adjusting airfare, they will lose passengers on routes with high-quality HSR service while gain passengers on routes with low-quality HSR services.

The third column of Table 2.8 presents estimation of airfare model Eq.(2.3). Right after HSR entry, airfare decreases on routes with TTD in between 3 and 9 hours, and the magnitude of the reduction diminishes as rail quality decreases, from a drop of USD 8.8 to a drop of USD 4.3. This part of the result is consistent with several previous studies in the literature, e.g., Wei et al. (2017) and Wang et al. (2018). However, different from the literature, we find that routes with the highest-quality HSR (TTD $<$ 3 hours) and the lowest-quality HSR (TTD $>$ 9 hours) do not

Table 2.8: Regression results with full sample

DepVar:	Pax		Fare
Models:	Eq.(2.1)	Eq.(2.2)	Eq.(2.3)
	(1)	(2)	(3)
Fare	-379.3***		
	(33.10)		
TTD<3h ($D1$)	-13,848***	-15,607***	4.827*
	(1,340)	(971.1)	(2.595)
3h<TTD<5h ($D2$)	-6,876***	-3,459***	-8.802***
	(848.6)	(579.7)	(1.541)
5h<TTD<7h ($D3$)	-390.8	1,731***	-5.132***
	(626.9)	(437.1)	(1.166)
7h<TTD<9h ($D4$)	-474.9	1,080***	-4.289***
	(590.1)	(419.1)	(1.120)
TTD>9h ($D5$)	3,645***	3,417***	2.509*
	(658.3)	(480.1)	(1.281)
Feeding	72.85***	76.15***	0.0606***
	(11.83)	(8.627)	(0.0206)
HSRmonth	156.5***	-92.72***	0.704***
	(28.77)	(13.75)	(0.0351)
LCCshare	-757.2	6,284***	-3.441
	(2,649)	(1,880)	(5.083)
RouteGDP	0.0807***	0.0251	
	(0.0291)	(0.0209)	
RoutePOP	3.141***	-0.501	
	(0.542)	(0.320)	
HHI			40.66***
			(2.586)
Constant	-4,120	36,047***	104.6***
	(10,885)	(7,519)	(1.369)
Three-way FE	✓	✓	✓
Observations	7,440	7,440	7,440
R-squared		0.259	0.326

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

experience airfare reduction. Rather, airfares seem to increase on these routes. For the routes with the highest-quality HSR presence, it is probably because airlines tend to give up the low-end passenger segment while focusing on the high-end segment, considering that it is too difficult to compete for passengers who have high price sensitivity and low value of time in a market where HSR provides reasonable quality at a much cheaper price.

The second column refers to OLS estimation of traffic model Eq.(2.2) which does not control for airfare. Comparing the coefficients of TTD dummies in Eq.(2.2) with those in Eq.(2.1), we find the coefficients of $D2$, $D3$ and $D4$ in Eq.(2.2) are substantially increased while those of $D1$ and $D5$ see a slight decrease. Since HSR's impact on airfare is proved by Eq.(2.3), we can conclude that HSR-induced airfare adjustment is a key channel of the post-entry air traffic change. On routes with TTD around 3-9 hours, HSR-induced airfare reduction, as shown in Eq.(2.3), leads to a statistically significant boost in air traffic. Post-entry airfare reduction mitigates the negative impact of HSR on air traffic by half on routes with TTD around 3-5 hours. More importantly, airfare reduction leads to an increase in air traffic on routes with TTD around 5-9 hours, though there would have been no observable traffic change on these routes if airfare were kept unchanged after HSR entry. On routes with TTD less than 3 hours, the post-entry airfare raise contributes to further air traffic reduction, which is evident from the slightly larger (in magnitude) coefficient of $D1$ in Eq.(2.2) than that in Eq.(2.1). Similarly, the mild increase in airfare on the routes with TTD above 9 hours slightly suppresses the air traffic increase in these routes.

2.5.2 Airline reactions to HSR feeding opportunities

We observe a strong positive impact of HSR feeding cities on air traffic in Table 2.8, suggesting that other than head-to-head competition on origin-destination (OD) passenger traffic, an air-HSR intermodal market emerges, adding traffic to aviation. Besides, this impact is not driven by airfare adjustment since the coefficients of $Feeding_{it}$ are quite similar in Eq.(2.1) and Eq.(2.2). This finding is consistent with Gu and Wan (2020), although the approaches to measure feeding effect are different. In fact, airfare increases with the number of feeding cities in Eq.(2.3) probably because HSR's ability to feed air routes enhances the demand for air transport.

2.5.3 Airline's long-term reactions

There is some evidence of long-term impact on both air traffic and airfare which is realized gradually over time after the entry of HSR. In the first column of Table 2.8, the positive coefficient of $HSRmonth_{it}$ implies that in addition to the competition effect and feeding effect immediately realized after the entry of HSR (captured by $D1_{it} \sim D5_{it}$ and $Feeding$), as time passes by, HSR operation tends to bring more traffic to airlines if airfare is unchanged. This might be interpreted by the increasing role of feeding effect over the competition effect as passengers become more aware of HSR and the benefit of intermodal trips as time goes by. It might also be caused by extra OD travel demand induced by HSR due to various possible reasons. For example, as people get more familiar with HSR services, some air passengers may become more willing to travel since HSR can serve as a back-up mode for delays or disruptions in air transport service. However, the statistically significant positive coefficient of $HSRmonth_{it}$ in the third column indicates that airfare also has an increasing trend as time elapses after HSR entry. It could be explained by airlines' strategy to gradually quit the low-end market and focus on high-end passengers who care more about travel time. The upward trend on airfare over time also echoes the notion of induced travel demand. Consequently, the net impact on air traffic in the long run is negative, as indicated by the negative coefficient of $HSRmonth_{it}$ in the second column of Table 2.8.

2.5.4 The role of pre-entry market structure

While HSR's impact on air traffic is largely channeled by airlines' price reactions, airlines' price adjustment, especially price reduction, could be determined by airlines' market power before the entry of HSR. For instance, airlines with strong market power before HSR's entry may enjoy a high markup, which provides room for airfare reduction as a response to HSR's entry. In other words, in addition to the varying HSR relative quality captured by TTD, the heterogeneous pre-entry airline market structure could lead to heterogenous airline reactions. The role of pre-entry market structure is investigated by estimating Eq.(2.1), (2.2) and (2.3) with two subsamples, one with pre-entry airline HHI below 0.3 presenting markets with high level of airline competition pre-entry and the other with pre-entry airline HHI over 0.3 presenting markets with low level of airline competition pre-entry.[8]

In the subsample of high pre-entry competition level, airfare increases regardless of the TTD ranges (Eq.(2.3) in Table 2.9). One possible explanation is that in a highly competitive market pre-entry, the competition among airlines might already keep airfare low, possibly close to the marginal cost, leading to a lean markup and no room for further price reduction after HSR enters the market.[9] Thus, airlines might react by giving up competing with HSR for the low-end market. Possible cost increases due to reduced traffic density may also contribute to the increase in price. The conjecture is that if airlines choose smaller aircraft because of reduced route-level demand after HSR entry, the unit cost (cost per seat) will increase, adding upward pressure on airfare. Thus, we conduct another regression analysis on aircraft size to see whether and how aircraft size changes after HSR entry.[10] The independent variables are the same as those in Eq.(2.2). The OLS estimation results are listed in the fourth column of Table 2.9. Clearly, aircraft size decreases in all cases of TTD, which is consistent to our conjecture. By comparing the coefficients of $D1 \sim D5$ in the first and second columns of Table 2.9, one can observe that such price increase further reduces air traffic for all ranges of TTD. That is, the net air traffic increase induced by airfare adjustment (as mentioned in Section 2.5.1) does not occur in markets where airlines compete fiercely before the entry of HSR. Only routes with TTD above 9 hours have an insignificant increase in traffic after fare adjustment (the second column of Table 2.9).

However, when the pre-entry competition level is low (Table 2.10), airfare only significantly increases on routes with TTD below 3 hours with a statistically significant

[8]Sensitivity checks regarding the cut-off HHI is presented in Appendix A.3.

[9]Using cost data released by Chinese big-three airlines (i.e., CA, CZ and MU), we compute the marginal cost for each airline-route pair following Zhang et al. (2014) and find positive relationship between HHI and markup. In addition, the mean markup of the routes with HHI below 0.3 is USD 5.9, which is substantially lower than that of the routes with HHI above 0.3 (USD 16.3).

[10]Aircraft size is measured by the average number of seats provided per flight. It possesses fair variations with the average value 157.1, the minimum value 74.5 and the maximum value 297.9.

Table 2.9: Regression results of routes with high level of competition pre-entry (HHI<0.3)

DepVar:	Pax		Fare	Aircraft size
Models:	Eq.(2.1)	Eq.(2.2)	Eq.(2.3)	
	(1)	(2)	(3)	(4)
Fare	-305.9***			
	(40.54)			
TTD<3h ($D1$)	-8,673***	-12,288***	8.891***	-3.643**
	(1,508)	(1,137)	(3.420)	(1.485)
3h<TTD<5h ($D2$)	-5,425***	-7,783***	6.314**	-3.528***
	(1,202)	(922.7)	(2.734)	(1.205)
5h<TTD<7h ($D3$)	-22.17	-1,724***	5.769***	-0.891
	(850.6)	(652.2)	(1.926)	(0.852)
7h<TTD<9h ($D4$)	-487.6	-1,856***	4.594***	-5.005***
	(737.3)	(568.3)	(1.696)	(0.742)
TTD>9h ($D5$)	1,979**	1,136	4.874**	-6.227***
	(958.1)	(756.6)	(2.272)	(0.988)
Feeding	81.82***	64.47***	0.0851***	0.107***
	(15.55)	(12.23)	(0.0324)	(0.0160)
HSRmonth	97.38***	50.86*	0.189**	-0.0575
	(34.35)	(26.87)	(0.0773)	(0.0351)
LCCshare	-929.5	5,075**	-1.392	-3.989
	(3,230)	(2,489)	(7.442)	(3.251)
RouteGDP	0.000342	-0.0365		-0.000145***
	(0.0430)	(0.0339)		(4.43e-05)
RoutePop	1.656**	-0.882*		0.000863
	(0.706)	(0.494)		(0.000645)
HHI			57.62***	
			(5.588)	
Constant	21,741	44,879***	99.27***	145.5***
	(14,700)	(11,432)	(2.234)	(14.93)
Three-way FE	✓	✓	✓	✓
Observations	2,592	2,592	2,592	2,592
R-squared		0.275	0.363	0.268
Number of routes	54	54	54	54

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

aircraft size reduction. On almost all the other route categories (TTD between 3 and 9 hours), airfare reduces, together with a slight (sometimes statistically insignificant) increase in aircraft size. This means as long as HSR is not sufficiently attractive in quality, airlines have incentives to compete with HSR by reducing the price as high pre-entry markup makes such price reduction possible. Such airfare reduction may lead to a net increase in air traffic post entry when TTD is around 5-9 hours (the second column of Table 2.10), similar to what we have found with the full sample in Section 2.5.1. On the other hand, if airfare were unchanged (the first columns of Tables 2.9 and 2.10), the parallel entry of HSR has a stronger traffic impact on routes with low pre-entry competition than those with high pre-entry competition. The possible reason is that fewer airlines were operating in the low competition market, providing limited travel options pre-entry. As a result, the new HSR service is more likely to be welcomed by passengers. The low pre-entry competition level group shows consistent results with the model estimated with the full sample. Consistent with findings in Section 2.5.1, the special reactions on routes with TTD > 9 hours are observed in both low and high pre-entry competition cases. That is, air traffic has increased after the entry of HSR in these markets together with some mild increase in airfare, despite that the magnitude of air traffic increase is much larger in the case of low pre-entry competition.

Similar to the findings in Section 2.5.2, the number of feeding cities is positively related to air traffic and airfare regardless of the pre-entry competition level. However, the magnitudes of these impacts are slightly larger in the high competition markets, probably because more airline options are available in such markets, making it easier to find flights with desirable air-rail connection time. Another interesting result is found in the long-term impact. $HSRmonth_{it}$ is associated with a smaller amount of airfare increase in markets with high pre-entry competition than those with low pre-entry competition. This difference in airfare adjustment makes the long-term air traffic effect positive in high pre-entry competition markets while negative in the other markets. These findings suggest if airlines possess little market power, air traffic is more likely to grow via either the HSR-induced travel demand over time or an increase in feeding cities as the HSR network expands.

2.5.5 Sensitivity check with 3SLS

As mentioned in Section 2.4, while airfare is expected to affect air traffic, the later can also affect the former. This relationship is well recognized as interdependency and simultaneity of quantity and price. We have addressed this endogeneity problem

Table 2.10: Regression results of routes with low level of competition pre-entry (HHI>0.3)

DepVar:	Pax		Fare	Aircraft size
Models:	Eq.(2.1)	Eq.(2.2)	Eq.(2.3)	
	(1)	(2)	(3)	(4)
Fare	-374.2***			
	(44.61)			
TTD<3h ($D1$)	-7,323***	-15,175***	21.00***	-7.692***
	(2,784)	(1,863)	(5.010)	(2.583)
3h<TTD<5h ($D2$)	-7,605***	-3,473***	-9.995***	2.806**
	(1,410)	(939.0)	(2.509)	(1.302)
5h<TTD<7h ($D3$)	-1,228	2,694***	-9.551***	1.112
	(1,004)	(631.4)	(1.700)	(0.876)
7h<TTD<9h ($D4$)	-1,444	1,380**	-6.753***	0.706
	(1,016)	(681.4)	(1.834)	(0.945)
TTD>9h ($D5$)	4,104***	3,303***	3.870**	6.489***
	(834.2)	(588.8)	(1.580)	(0.816)
Feeding	55.08***	62.92***	0.0748***	0.0776***
	(16.64)	(11.81)	(0.0283)	(0.0164)
HSRmonth	163.5***	-50.38**	0.623***	-0.0683*
	(43.97)	(25.45)	(0.0660)	(0.0353)
LCCshare	-1,975	6,464***	-10.16	1.523
	(3,658)	(2,499)	(6.806)	(3.465)
RouteGDP	0.174***	0.0657**		-0.000238***
	(0.0401)	(0.0270)		(3.74e-05)
RoutePop	3.702***	1.139***		-0.00184***
	(0.671)	(0.424)		(0.000588)
HHI			38.11***	
			(3.225)	
Constant	-21,818	-4,020	118.6***	227.2***
	(13,445)	(9,433)	(1.853)	(13.08)
Three-way FE	✓	✓	✓	✓
Observations	3,984	3,984	3,984	3,984
R-squared		0.311	0.338	0.144
Number of routes	83	83	83	83

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

between airfare and air traffic by estimating Eq.(2.1) with 2SLS, which is sufficient to address related estimation bias for our research objective, because we focus on the comparison of two air traffic equations, i.e. Eq.(2.1) and Eq.(2.2), as well as the mediation effect of airfare on air traffic. In this case, the impact of HSR on airfare modeled in Eq.(2.3) can be considered as the total effects combining HSR's direct impact on airfare and HSR's indirect impact on airfare through air traffic change.

However, if one would like to further examine the airfare equation by exploring an indirect mechanism behind HSR's impact on airfare through the change of air passenger volume, other than HSR's direct impact on airfare, we can use three-stage least square (3SLS) method. The above idea is illustrated in Figure 2.2. Airlines' reactions to HSR entry can form an economic loop. First, HSR can affect airfare and air traffic directly, as shown by (i) and (ii). Then, the direct impact on airfare can be further passed onto air traffic indirectly as shown by (iii). Meanwhile, the direct impact on air traffic can be further passed onto airfare indirectly as shown by (iv).

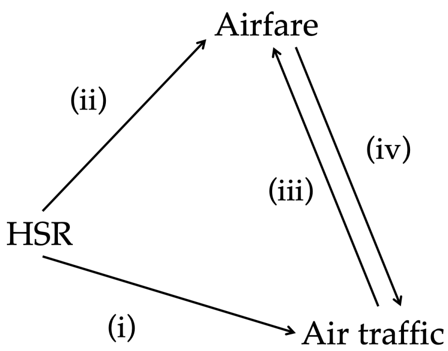


Figure 2.2: Illustration of HSR impact

In this section, we show that applying the 3SLS does not change our main findings about how HSR affects air traffic and the mediation role of airfare. In detail, we modify Eq.(2.3) into Eq.(2.4) by adding Pax_{it} as a predictor of airfare. As air traffic is controlled in Eq.(2.4), HSR variables in this equation now capture the direct effect on airfare that is irrelevant to passenger number change.

$$\begin{aligned} Fare_{it} = \delta_0 + & \sum_{m=1}^{5} \delta_m Dm_{it} + \delta_6 Pax_{it} + \delta_7 Feeding_{it} + \delta_8 HSRmonth_{it} \\ & + \delta_9 LCCshare_{it} + \delta_{10} HHI_{it} + route_i + year_t + month_t + \xi_{it} \end{aligned} \tag{2.4}$$

We treat Eq.(2.1) and Eq.(2.4) as a system of simultaneous equations and estimate this equation system with 3SLS procedure, which combines the 2SLS process and the seemingly unrelated regression approach (Zellner and Theil, 1962). After identifying the coefficients for the equation system, we can solve the simultaneous equations to generate each variable's total impact (direct plus indirect) on air traffic and airfare, respectively. The computational procedure of individual variables' total impacts is presented in Appendix A.4.

Regression results using 3SLS and individual variables' total impacts are listed in Table 2.11. Comparing the first column in Table 2.11 and the first column in Table 2.8, which identify the direct effect of HSR under two different economic perspectives, we find that 3SLS makes little change on the estimated direct effects on air traffic. All the coefficients of HSR related variables show the same sign and similar magnitude. The total impacts estimated from the two methods are consistent as well. This can be seen by comparing the second column in Table 2.8 and the third column in Table 2.11 for the total impacts of HSR on air traffic and comparing the third column in Table 2.8 and the fourth column in Table 2.11 for the total impacts of HSR on airfare. These observations imply that using 3SLS does not affect the identification of the role of airfare adjustment in HSR's impact on air traffic.

2.6 Policy implications

HSR has been advocated by policy makers because it emits less greenhouse gas (GHG) such as CO2 and NOx than air transport on a per-seat basis (e.g., European Commission, 2011; Transportation Research Board, 2013). Substituting air flights by HSR on short-haul routes may benefit the environment. However, in Section 2.5, using data from the Chinese markets, we find that although HSR entry reduces traffic in many overlapping air routes, HSR can increase air traffic in three ways. First, it enhances the intermodal market. Second, HSR may induce extra demand for air travel in the long term or in markets with TTD $>$ 9 hours. Third, substantial post-entry airfare reduction could occur in markets with relatively low HSR quality (i.e. TTD between 5 and 9 hours) or low pre-entry intra-modal competition, resulting in an increase in air traffic on these routes. The third channel can further complicate the long-term effect mentioned in the second channel as airfare could increase in the long term which counteracts the induced air travel demand. With air traffic increasing and decreasing on different routes, it is unclear whether HSR will lead

Table 2.11: Regression results with 3SLS approach (full sample)

	DV=Pax Eq. (1)	DV=Fare Eq. (4)	Total impact on air traffic	Total impact on airfare
	(1)	(2)	(3)	(4)
Fare	-378.4***			
	(32.67)			
Pax		-0.00991*		
		(0.00601)		
TTD<3h ($D1$)	-13,667***	-143.4	-14,765.61***	2.904
	(1,320)	(90.43)	(953.8)	(2.566)
3h<TTD<5h ($D2$)	-6,695***	-39.92**	-3,057.9***	-9.611***
	(834.5)	(19.71)	(565.7)	(1.554)
5h<TTD<7h ($D3$)	-332.3	10.78	1,603.4***	-5.115***
	(618.3)	(10.56)	(423.6)	(1.151)
7h<TTD<9h ($D4$)	-485.9	5.766	969.97**	-3.847***
	(582.4)	(7.361)	(407.6)	(1.098)
TTD>9h ($D5$)	3,763***	33.01*	3,173.3***	1.559
	(648.0)	(19.09)	(472.0)	(1.277)
Feeding	83.42***	0.829*	83.76***	-0.00089
	(10.90)	(0.472)	(9.477)	(0.2985)
HSRmonth	167.4***	-0.0870	-72.81***	0.634***
	(28.08)	(0.497)	(14.29)	(0.041)
LCCshare	-362.2	11.44	1,705.7	-5.464
	(2,609)	(20.77)	(1,856)	(5.049)
RouteGDP	0.0358		-0.013	0.00013
	(0.0226)		(0.0176)	(.0001)
RoutePOP	2.489***		-0.904	0.00897***
	(0.469)		(0.6562)	(0.0013)
HHI		-110.1	-15,151.76***	40.04***
		(91.95)	(939.6)	(2.535)
Constant	17,251**	472.0**		
	(7,292)	(221.7)		
Three-way FE	✓	✓		
Observations	7,440	7,440		

Notes: The first and second columns represent HSR's direct impacts. The first column is comparable to the first column in Table 2.8. The third and fourth column represent HSR's total impact and are comparable to the second and third columns in Table 2.8. Standard errors in parentheses. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

to less GHG emissions from air transport. Thus, we conduct the counterfactual analysis to decompose HSR-associated traffic changes and discuss the implication of air traffic changes on airlines' CO2 emissions. As aircraft's CO2 emission rates (CO2 emission per passenger) vary in routes, we compute CO2 emission change for each route in each month and present the aggregated results for routes in our sample.

2.6.1 Air traffic and emission effects with airfare adjustment

Regression results obtained from Eq.(2.2) in Table 2.8 are used to calculate counterfactual net air traffic change, summing up fare-relevant and fare-irrelevant effects. The net changes in air traffic on route i at time t are expressed in Eq.(2.5). The first component captures the immediate traffic change due to competition with HSR of varying quality (TTD). The second component captures the traffic change due to feeding effect, while the third component represents the long-term traffic change over time.

$$\Delta Pax_{it} = \sum_{m=1}^{5} \hat{\beta}_m Dm_{it} + \hat{\beta}_7 Feeding_{it} + \hat{\beta}_8 HSRmonth_{it} \tag{2.5}$$

CO2 emission change is computed as

$$\Delta E_{it} = \gamma_i \Delta Pax_{it} \tag{2.6}$$

where γ_i is the average CO2 emission rate of route i retrieved from the ICAO Carbon Emissions Calculator. The emission rate refers to the average CO2 emissions per economy-class passenger for a one-way trip on a certain route. According to ICAO, the calculator applies industry data to account for various factors such as aircraft types, route-specific data, passenger load factors and cargo carried.[11] The average CO2 emission rates of all sampled routes are listed in Appendix A.5.

Surprisingly, HSR introduced a large amount of air traffic in the study period. Adding up all affected air routes in the sample over the four years, we find HSR introduced over 16.5 million new air passenger trips, accounting for 6% of the total air traffic of all sample routes in the four-year study period. This number includes the induced demand on very long-haul routes and the feeding traffic. In total, aviation emitted more than 2.17 million tons of extra CO2 due to HSR operation during the 2012-2015 period. The variation at route-level can be huge. For example, on an average route facing the highest quality HSR entry (i.e. TTD $<$ 3 hours), airlines would lose 189,490 passengers during the first year of HSR entry, while on

[11] Refer to ICAO Carbon Emissions Calculator Methodology for details.

an average route with the weakest HSR service (i.e. TTD > 9 hours), airlines may gain 38,797 passengers.

Table 2.12 presents the monthly traffic change averaged across routes by year and route type and monthly CO2 emission change averaged across all sampled routes by year. Note that air routes without parallel HSR entry (non-HSR routes) also experience traffic and emission changes as these routes are fed by HSR as long as one of the endpoint cities is linked to other cities by HSR and the intermodal transfer time is within the feasible connection window. Although air transport on average loses substantial traffic and reduces emissions on routes with TTD below 5 hours, the increase in aggregated traffic and emission comes from the larger share of routes with TTD over 5 hours and non-HSR routes. This alerts us to the essence of examining the mix of routes when evaluating the system-wide (or country-wide) emission impacts. In the context of China, as the HSR system continues expanding in the future, more long-haul air routes will encounter HSR entry, and the number of feeding cities will further increase. Thus, it is possible that the future HSR development will continue pushing domestic air traffic and airline emissions upward.

Table 2.12: Average monthly changes in air traffic and CO2 emission by year and route type

	Air traffic change							CO2 emission change (kg, all route types)
	TTD					Non-HSR routes	All route types[b]	
Year	<3h	3-5h	5-7h	7-9h	>9h[a]			
2012	-15,568	-4,014	1,654	221		2,066	1,169	161,041
2013	-15,382	-1,647	3,032	5,762		3,028	1,996	260,353
2014	-15,841	-2,374	3,115	4,860	7,203	2,896	1,904	267,237
2015	-13,110	-721	5,576	7,010	9,262	4,480	3,806	492,003

Notes: [a] In 2012 and 2013, no observations fall into this category. [b] This column shows the monthly changes in air traffic averaged across all routes.

To understand the main sources of the overall positive traffic changes in our sample, the HSR-associated effect averaged across all sample routes is decomposed into three parts (Table 2.13). The competition effect refers to the immediate traffic changes due to parallel HSR entry captured by coefficients of TTD dummies. This effect is negative across all years, suggesting that although routes with TTD over 5 hours (i.e., those experiencing positive competition effect) account for a larger share of the sample routes, the negative competition effect on routes with TTD below 5 hours outweighs. Moreover, the sample routes also experience extra traffic reduction in the long term as airfare has an upward trend over time. However, these two negative effects are counteracted by the huge positive values of the feeding effect, leading to an overall positive traffic effect.

Table 2.13: Decomposition of monthly total HSR impact on air traffic by year

Year	Competition	Feeding	Long term	Total
2012	-554	2,270	-547	1,169
2013	-703	3,459	-759	1,997
2014	-584	3,587	-1,099	1,904
2015	-543	5,939	-1,590	3,806

Notes: Each cell presents the average monthly air traffic change associated with each effect. "Total" column presents the average monthly air traffic change combining the three effects. It is equal to the "All route types" column in Table 2.12.

Our result is different from Strauss et al. (2021) who also evaluates HSR's impact on air traffic and CO2 emissions in China. They conclude that mode substitution from air flights to HSR leads to 18% reduction in air carbon emissions. The difference mainly comes from the omission of HSR's feeding effect in Strauss et al.'s study. As HSR network expands and airlines promote air-rail intermodal services, the feeding impact will be increasingly significant.

2.6.2 Price-irrelevant air traffic and emission effects

As shown in Section 2.5, post-entry airfare adjustment substantially influences air traffic changes, and such adjustment varies in pre-entry market structure and rail quality. Thus, it is useful to quantify HSR-related air traffic and emission changes that are irrelevant to airfare adjustment and see how airfare adjustment would alter the results. The approach of calculating price-irrelevant effects is similar to Eq.(2.5) and Eq.(2.6), except that the calculation is based on the estimation of Eq.(2.1) in Table 2.8 instead of Eq.(2.3).

The total effect and price-irrelevant effect are compared in Table 2.14. If airfare remained unchanged after HSR entry, the monthly air traffic increase would have almost doubled. Combining all the sampled routes in the study period, HSR would introduce around 32.2 million additional passengers (11.7% of the total air traffic of the sampling period) and 3.4 million tons of extra CO2 emissions after excluding price-relevant effects. This results from the significant upward pressure of long-term impact after removing the influence of airfare adjustment, together with the positive feeding effect, which outweighs the negative competition effect. Note that if airfare is allowed to change after HSR entry, airlines tend to increase airfare which reduces traffic in the long term (Table 2.13). Therefore, the total effect that sums up price-relevant and price-irrelevant effects results in less traffic growth. The price-irrelevant effects of different route types are provided in Appendix A.6.

Table 2.14: Decomposition of monthly price-irrelevant HSR impact on air traffic by year

	Traffic change					CO2 emission change (kg)	
	Price-irrelevant				Total[b]	Price-irrelevant	Total[b]
Year	Competition	Feeding	Long term	Sum[a]			
2012	-804	2,171	923	2,290	1,169	251,737	161,041
2013	-1,196	3,309	1,281	3,394	1,997	371,124	260,353
2014	-1,245	3,432	1,855	4,042	1,904	447,107	267,237
2015	-1,320	5,682	2,684	7,046	3,806	779,736	492,003

Notes: [a] The "Sum" column under "Price-irrelevant" refers to the sum of competition, feeding and long-term impacts after controlling for airfare, i.e. based on Eq.(2.1). [b] The "Total" columns under "Traffic change" and "CO2 emission change" add up price-irrelevant effect and price-relevant effect, replicating the values of "all route types" in Table 2.12.

Table 2.15 presents traffic changes under different market structures. When airfare keeps constant, markets with high level of competition pre-entry experience a stronger traffic increase than those with low level of competition. However, price adjustment pivots this result. As HSR entry tends to increase airfare in high competition markets while reduce airfare in low competition markets, the overall traffic increase (as shown in the "Total" columns) is much milder in the former than in the latter. In other words, the price-relevant effect is negative in high competition markets but tends to be positive in low competition markets. The difference between these two kinds of markets becomes larger as HSR expands the network over time.

In sum, the introduction of HSR would generally boost air traffic, mainly by feeding intermodal passengers and inducing long-haul market demand, resulting in more

CO_2 emissions. Note that our calculation only considers the impacts on air traffic and airline emissions. The emission increase can be further enlarged if emissions from power generation to support HSR operation are also included. That is, the 2.17 million airline CO_2 emission increase during the sampling period (estimated in Section 2.6.1) might be considered as a lower bound of system-wide CO_2 emission change which adds up CO_2 emissions from airlines and HSR.

Table 2.15: Average monthly traffic change by pre-entry competition level and model

	High pre-entry competition		Low pre-entry competition	
Year	Price-irrelevant	Total	Price-irrelevant	Total
2012	2,015	1,452	1,460	1,640
2013	3,207	2,193	1,923	2,423
2014	3,518	2,016	2,457	2,649
2015	6,094	3,716	4,956	4,556

Notes: "Price-irrelevant" columns show the effects based on Eq.(2.1), while the "Total" columns present the effects based on Eq.(2.2), which add up price-irrelevant effect and price-relevant effect.

Our analysis also demonstrates substantially different results when post-entry airfare adjustment is taken into account. During our study period, without airfare adjustment, the extra airline CO_2 emissions induced by HSR would grow by over 35%. However, the power of airfare adjustment pivots on market structure, in the sense that overall air traffic and emission will decrease through price adjustment only when the pre-entry airline competition is intensive. This calls for serious assessment on airlines' reaction in price by policy makers in various regions as airline competition intensity could vary significantly across different domestic markets. The assessment on price response also has implications on air passengers' consumer surplus. Intuitively, consumer surplus of individual air passengers would be harmed in highly competitive airline markets as airfare tends to increase after HSR entry. On the contrary, passengers may be better off in markets where airlines possess certain market power before HSR entry.

2.6.3 Airfare regulation

Civil aviation administration of China (CAAC) has been progressively lifting airfare regulation in recent years as summarized in Appendix A.7. Since 2004, carriers were allowed to set airfare at most 25% more than or 45% less than the base fare set by the government. The price floor and the price cap were then removed for the first and business classes with effect from 1 June 2010 and the price floor was further removed for all classes on 20 October 2013. This means carriers can set prices as low as they wish starting from late 2013. Meanwhile, for routes that compete with ground transportation modes and are served by two or more air carriers, the price cap was also removed. In late 2014, the calculation method for base fare was revised, allowing for a higher unit price per kilometer on short-haul routes. Besides, routes connecting cities in two adjacent provinces and facing competition from ground transport were allowed to freely set prices since 15 December 2014. At the end of 2016, free pricing was extended to routes with travel distance below 800 km, as well as routes with travel distance above 800 km and served by HSR. Then, free pricing was extended to air routes served by five or more carriers in 2017 and was further extended to routes operated by three or more carriers in 2020, regardless of the presence of competition from ground transportation.

Our research period 2012-2015 covers the implementation period of the 2013 and 2014 liberalization. While all routes were no longer restricted by the price floor since late 2013, in our sample, only 17 out of 155 city pairs were affected by the removal of price cap in 2013 and 2014. That is, the majority of our sample routes and sample periods were restricted by the 2004 regulation, and airlines had some but limited freedom to set prices. Nevertheless, we can still observe the strong role of HSR-induced airfare adjustment in counteracting air traffic growth, as discussed in Section 2.6.2.

This calls for the discussion on what might happen after our sample period, given that the price cap deregulation has been sped up after 2016. Recall the regression results of long-term impact. Airfares tend to increase as time passes by after HSR entry. This might suggest that with more freedom to increase the airfare, airlines are likely to raise the airfare to an even higher level. As the price cap of more routes has been removed since 2016, we conjecture that the chance and the amount of airfare raise is likely to be elevated. Besides, with rapid development of HSR in China, the number of HSR feeding cities would further increase, posing another upward pressure on airfare. This upward pressure also exists on the routes where airlines have competitive advantage, e.g. routes with TTD > 9 hours, even when the long-term and feeding effects are excluded. Thus, we expect individual passenger's welfare of traveling by air are likely to be reduced in more recent years due to further airfare increase. However, this effect can be social-welfare enhancing, as HSR-induced air traffic growth can be fairly mitigated by raising airfare, which helps with reducing CO2 emissions from air transport.

2.7 Concluding remarks

This study empirically examines whether airfare adjustment contributes to some observed air traffic increases after HSR entry. We also investigate airlines' heterogeneous reactions due to different HSR qualities and market structures. We find that airfare declines on routes with TTD between 3 hours and 9 hours. Such price reduction is the main source of air traffic increase on routes with TTD between 5 and 9 hours. Although the total (net) effect on routes with TTD between 3 and 5 hours is negative, airfare reduction relieves half of the negative impact. Without airfare adjustment, on route with TTD below 5 hours, passengers might shift mode preference to HSR, possibly for HSR's less access/egress time and excellent on-time performance. In terms of market structure, airlines are found to increase airfares if pre-entry inter-airline competition is intensive and cut airfares if pre-entry competition is light. Thus, price adjustment enhances air traffic reduction in high competition market while moderates air traffic reduction (or even raise air traffic) in low competition market. While the feeding effect is found not channeled by airfare adjustment, the long-term effect may turn negative if price adjustment is taken into account. It is worth noting that the routes with no HSR presence during 2012-2015 also receive extra traffic due to HSR's feeding effect.

Overall, the feeding effect dominates in our sample. In general, airlines lose traffic in the market where HSR quality is very high and gain traffic in the markets where HSR quality is low. Combining competition effect, feeding effect and long-term effect as well as effects of price adjustment, we find HSR introduced over 16.5 million additional passengers to the aviation sector, accounting for 6% of the four-year total traffic of the sample routes. This is equivalent to 2.17 million tons of extra CO2 emissions from airlines. However, these numbers would increase to 32.2 million additional passengers (11.7% of the total air traffic of the sampling period) and 3.4 million tons of extra CO2 emissions after excluding price-relevant effects.

Our study is limited in the following aspects. First, in analyzing air-rail competition, ticket price of HSR is also an important factor. Although HSR ticket price in China was highly regulated till 2016 and hence almost fixed and determined by the travel distance during our study period (Li et al., 2019a), which is partially captured by TTD, explicit modeling of HSR traffic and price, together with air traffic and airfare, will provide a more comprehensive understanding on the interaction between HSR and airlines, especially because regulators in China have gradually removed control on HSR ticket prices since 2016. Second, without explicit modeling of HSR traffic, we are not able to conduct a clear assessment on HSR's impact on consumer surplus, despite that airfare has been found to increase in some cases while decrease in the other. Third, a complete evaluation on HSR's impact on CO2 emissions requires an assessment on not only changes in airlines' CO2 emission but also CO2 emissions of HSR operation to serve passengers diverted from airlines and induced trips of intermodal service. Fourth, the interaction between aircraft size and flight frequency as a reaction to HSR entry is another relevant issue. A separate investigation on this issue might provide additional insights on the channels of HSR impacts to complement this study. Finally, due to data availability, we cannot provide formal and rigorous tests on why airlines increase fares after HSR entry on some markets. Future investigations on reasons for this phenomenon would help better understand airlines' behaviors.

Chapter 3

Airline departure-time differentiation under HSR competition

3.1 Introduction

Since its first launch in China, HSR has been experiencing rapid growth. During the ten years between 2010 and 2019 before the COVID-19 pandemic, HSR traffic measured by passenger kilometers has increased by more than 16 times in China (International Union of Railways, 2023). Literature on HSR's impact on air transport also booms. Vast papers discuss the impact from the perspectives of price, traffic, seat capacity provision and service quality (e.g., on-time performance) (e.g., Jiménez and Betancor, 2012; Yang and Zhang, 2012; Albalate et al., 2015; Wan et al., 2016; Chen, 2017; Zhang et al., 2018; Li et al., 2019a; Gu and Wan, 2020, 2022; Jiang et al., 2022), while little attention is paid on airline scheduling, although it is one of the most important strategic factors airlines consider . The temporal locations of flights have a direct impact on passengers' schedule delays and thus consumer welfare.

The location theory of product differentiation provides some implications, but opposite behaviors are predicted: when competition increases, firms can locate either farther away from competitors to mitigate price competition or closer to rivals to steal customers (Prescott and Visscher, 1977; d'Aspremont et al., 1979; Palma et al., 1985; Martinez-Giralt and Neven, 1988). In the airline industry, different flight departure (or arrival) times are commonly viewed as a type of product differentiation. Some researchers have empirically studied which behavior in practice is adopted by airlines. They consistently find that airlines tend to cluster the flights with increased competition, reducing differentiation (Salvanes et al., 2005; Yetiskul and Kanafani, 2010; Sun, 2015). In the literature, competition mainly comes from the same industry and hence competitors are close substitutes. However, none of the studies give an insightful understanding and prediction on the impact of HSR, a competitor from a different industry, on airline scheduling.

The inter-modal competition induced by the entry of HSR has several major differences from the changes in market structure within the airline industry or the entry of low-cost carriers (LCC). First, HSR is a rival outside of the airline industry and thus the market structure within the airline industry cannot fully reflect the competition from HSR. Second, HSR has varying competitive advantages compared with airlines. On short-haul routes, it has strong advantages in total trip time, given that the short access/egress time and terminal processing time can offset the long in-vehicle time, in addition to comfortable seats, better on-time performance, and convenient locations of HSR stations. In contrast, on long-haul routes, HSR takes much more time than flights and thus possesses little advantage over airlines. However, LCC tends to be a worse-off competitor to full-service carriers (FSC) in all markets, especially in terms of service quality. In another respect, HSR brings varying demand shocks at different times of the day. On long-haul routes, most HSR services cannot depart in the evening because of the long travel time, so HSR poses less competitive pressure on the evening flights compared with morning flights. Comparatively, LCC has a similar travel time with FSC and hence introduces a constant demand shock.

Third, FSC may conduct strategic actions in response to LCC entry threats. That is, FSC has the motivation and ability to deter LCC entry (Bet, 2021). However, HSR entry cannot be deterred in China. The HSR network is determined mainly by the central government while considering the needs and financial conditions of local governments, aiming primarily at encouraging intercity travel, releasing conventional railway capacity to freight trains and boosting economies. Profit is not the only pursuit of HSR operators. To provide a wide coverage of HSR services is also important. As a result, the entry of HSR services on a certain route rarely depends on airlines' behavior and would not be successfully deterred by airlines' actions. This might make airlines adopt different strategies when facing HSR competition compared with LCC entry. Thus, considering the three points, the results of LCC entry cannot be simply applied to HSR entry in all markets.

The seminal work by Borenstein and Netz (1999) proposes to proxy differentiation by the average distance between flights' departure times. Conditional on the set of flights considered, the market-level overall differentiation, between-airline differentiation, and within-airline differentiation are evaluated.[1] Most papers put emphasis on the impact on the overall differentiation, overlooking potentially different interactions between airlines and between flights within the same airline. Within-firm and between-firm differentiations reflect airlines' distinct strategies and could affect social welfare in different ways. An increase in within-airline differentiation means passengers have more schedule options to choose from, thus enhancing social welfare, while an increase in between-airline differentiation is normally accompanied by a rise in ticket prices, which can harm consumer surplus and probably social welfare. Thus, distinguishing the source of changes in overall differentiation is important in evaluating the impact on social welfare. Meanwhile, understanding the motivations behind the changes in these types of differentiation is helpful in future evaluations such as anti-trust investigations.

This chapter aims to bridge the research gap by investigating the impact of HSR on airline flight departure-time differentiation. Other than applying the measure of differentiation proposed by Borenstein and Netz (1999), we add another type of differentiation, namely closest between-airline differentiation, which evaluates the

[1]Overall differentiation considers all flight pairs, between-airline differentiation considers flights from different airlines, and within-airline differentiation considers flights from the same airline.

distances between airlines and their nearest competitors. The rationale is that considering passengers' preferred departure times, a flight has the strongest substitutability to the rival airline that has the closest departure time. As the between-airline differentiation applied in the literature may be affected by the within-airline departure time distribution, the closest between-airline differentiation is more capable of capturing the product differentiation with the immediate and most relevant rivals. The heterogeneous impacts of HSR are investigated from the perspectives of route distance and slot-control status. Then, we provide discussions on the possible motivations behind airline behaviors.

We focus on analyzing airline flight schedules throughout a day, based on which the differentiation indices are calculated. We employ a fixed effect regression model to identify HSR's impact and the heterogeneous impacts are estimated by subsample regressions.

The results show that airlines tend to get farther away from their adjacent competitors in the slot-controlled and long-haul markets. We propose that this behavior originates from airlines' ability and profitability of conducting differentiation strategies. In slot-controlled airports, airlines cannot freely change flight schedules unless swapping slots with other flights, and hence, the rival airlines cannot easily adjust their schedule when one airline reschedules its flights. This makes it feasible to differentiate with rivals by adjusting schedules. Besides, the slot-controlled markets tend to be supply-constrained and are more likely to maintain a high level of air travel demand relative to flight supply after HSR entry. This increases the chance of restoring profitability and hence the incentives to differentiate from other airlines upon the entry of HSR. Similarly, on long-haul routes, air travel demand won't be largely affected if airlines deploy a differentiation strategy and increase the price since they enjoy a competitive advantage over HSR.

Within-airline differentiation is found to be reduced in the short-haul and non-slot-controlled markets. We argue that it is because air travel demand experiences the largest drops in these markets, making it difficult to fill flights departing at less popular times, such as the early morning and late evening. Thus, airlines move these flights to the middle of the day or simply drop these flights, resulting in a decrease in within-airline differentiation. In general, the impact on within-airline differentiation outweighs that on between-airline differentiation, indicating that airlines tend to cluster flights together. Combining the findings above, we argue that when facing HSR competition, airlines have very limited strategies in terms of schedule designs. Moving to a popular time is probably a better and easier option than differentiating from others.

The rest of the chapter is organized as follows. Section 3.2 introduces the construction of varibales and samples and the empirical model. Section 3.3 report the estimation results and section 3.4 concludes the chapter.

3.2 Methodology

This section introduces the construction of differentiation indices, econometric models, data sources, and sample formations.

3.2.1 Measuring departure-time differentiation

One of the main tasks of the chapter is to evaluate product differentiation in terms of flight schedule. As air travel time is relatively stable during the sample years, the distribution of departure times is similar to that of arrival times. We choose to base our analysis on locations of flight departure times of a certain market throughout a day, considering one day as a 24-hour circle.[2] Suppose there are N_{mt} flights in market m on a representative day of sampling period t, each with departure time located at k, measured in minutes elapsed from midnight. In the spirit of Borenstein and Netz (1999), we measure differentiation with the average distance among a certain set of flights in the market. The distance between two flights (i, j) is determined by the minimum distance along the circle, as expressed in Eq.(3.1). Then, the overall differentiation of market m is obtained by Eq.(3.2) which presents the average dis-

[2]This assumption treats a flight in the late evening and another one in the early morning on the other day as a substitute.

tance of all the flight pairs with $\mathcal{F}$ denoting the set of all the flights of market m. $\alpha \in [0, 1]$ denotes the discount rate, which discounts longer distances. For ease of understanding and explanation, we take the value of one for α in the following analysis.[3] This overall differentiation, denoted as D_{mt}, does not distinguish an airline's flights and its rivals' flights. Thus, it measures the *industry*-level differentiation of a specific route market and cannot be used to analyze specific interactions among distinct airlines.

$$d_{i,j} = min\left\{|k_i - k_j|, 1440 - |k_i - k_j|\right\} \tag{3.1}$$

$$D_{mt} = \frac{2}{N_{mt}(N_{mt} - 1)} \sum_{j>i}^{N_{mt}} \sum_{i=1}^{N_{mt}-1} d_{i,j}^{\alpha} \qquad i, j \in \mathcal{F}_{mt} \tag{3.2}$$

We are most interested in how airlines set their own flight departure times and how they interact with competitors, so we construct the differentiation index at the airline level. Instead of treating all kinds of flight pairs as identical, we differentiate those of the same firm and those of different firms to construct within-firm differentiation and between-firm differentiation, respectively. Eq.(3.3) calculates the average distance between flights operated by the same airline l, indicating within-airline differentiation level. n_{lmt} denotes the number of daily flights operated by airline l in market m observed at sampling period t. Between-airline differentiation of airline l is measured by the average distance between every flight i of airline l and every flight j of airline l's rivals, shown as Eq.(3.4).

$$WD_{lmt} = \frac{2}{n_{lmt}(n_{lmt} - 1)} \sum_{j>i}^{n_{lmt}} \sum_{i=1}^{n_{lmt}-1} d_{i,j}^{\alpha} \qquad i, j \in \mathcal{F}_{lmt} \tag{3.3}$$

$$BD_{lmt} = \frac{1}{n_{lmt}(N_{mt} - n_{lmt})} \sum_{j=1}^{N_{mt}-n_{lmt}} \sum_{i=1}^{n_{lmt}} d_{i,j}^{\alpha} \qquad i \in \mathcal{F}_{lmt}, j \in \mathcal{F}_{-lmt} \tag{3.4}$$

Apart from the literature that focuses on average distances of all rival flight pairs, we introduce another index, BD^{cls}, aiming at studying schedule interactions between

[3]The results do not qualitatively change across different values of α.

the closest rivalries. For a flight i from airline l, we search for the nearest rival flight provided by another airline and calculate the distance between the two according to Eq.(3.1) and denote it as bd_cls_{li}.[4] Then we take average of such distances across all flights by airline l. The formal expression of the closest between-airline differentiation is provided in equation below.

$$BD^{cls}_{lmt} = \frac{1}{n_{lmt}} \sum_{i} bd\_cls^{\alpha}_{li} \tag{3.5}$$

To better facilitate the understanding of the index construction, we take the daily departure times of flights from CAN (Guangzhou Baiyun International Airport) to CKG (Chongqing Jiangbei International Airport) in November 2008 as an example, shown in Table 3.1. There are three airlines - Sichuan Airlines (3U), Air China (CA) and China Southern Airlines (CZ) in the market. Each provided three flights, with departure time listed in the second column. WD of 3U, for example, is calculated by $((995-625)+(1295-625)+(1295-995))/3$ and BD^{cls} equals to $(20+10+180)/3$, while BD is the average distance of nine 3U-CA flight pairs and nine 3U-CZ flight pairs.

Table 3.1: Example of Index Calculation

Airline	Departure Time	k	WD	BD	Closest rivalry	bd_cls	BD^{cls}
	10:25	625			CA 10:45	20	
3U	16:35	995	446.67	300.83	CA 16:25	10	70
	21:35	1295			CA 18:35	180	
	10:45	645			3U 10:25	20	
CA	16:25	985	313.33	279.17	3U 16:35	10	13.33
	18:35	1115			CZ 18:25	10	
	8:05	485			3U 10:25	140	
CZ	13:30	800	413.33	303.33	CA 10:45	155	101.67
	18:25	1105			CA 18:35	10	

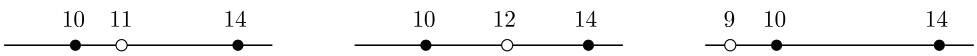
Notes: k corresponds to minutes elapsed from midnight of each departure time. Source: OAG Schedules Analyzer

One of the contributions of this study is to explicitly distinguish different types of differentiation. Especially, the pooled between-airline differentiation BD and

[4]Note we do not distinguish rival airlines with this measure, so for different focal flights, the closest rival flight can come from different airlines.

the closest between-airline differentiation BD^{cls} reveal different aspects of schedule distribution. BD captured the overall between-firm differentiation, considering all the rival flights, while BD^{cls} depicts a clearer picture of how flights move towards/against their head-to-head competitor. The two indices don't necessarily change in the same direction. It can be the case that one varies while the other remains.

To give an example, Figure 3.1 illustrates how BD and BD^{cls} change with different schedule settings. The line represents a segment from the 24-hour circle and each dot on the line represents the departure times of flights. Solid and empty dots distinguish airlines. Denote them as Airline S and Airline E, respectively. In the three cases, the locations of Airline S's flights are fixed at 10:00 and 14:00, while the departure time of Airline E's flight moves from 11:00 to 12:00 and 9:00, respectively. BD and BD^{cls} for each airline under the three cases are listed in Table 3.2. Comparing the first and second cases, the pooled between-firm differentiation indices for both airlines do not change, while the closest between-firm differentiation index for Airline E is increased by one hour. Turn to look at cases 1 and 3. Although for Airline E, the closest between-firm differentiation remains, the pooled between-firm differentiation increases because Airline E's flight moves farther away from Airline S' 14:00 flight.



(a) case 1 (b) case 2 (c) case 3

Figure 3.1: Differences between BD and BD^{cls}

Table 3.2: Between-firm differentiation of example cases

Case	Airline	BD	BD^{cls}
1	S	120	120
	E	120	60
2	S	120	120
	E	120	120
3	S	180	180
	E	180	60

Notes: The unit of BD and BD^{cls} is minutes.

3.2.2 Econometric models

We investigate airlines' reaction to HSR operation and its heterogeneity by panel data regression model. The main specification is shown in Eq.(3.6), where lmt represents the observations of airline l in the market m at time t.

$$Y_{lmt} = \beta HSR_{mt} + \zeta X_{lmt} + \lambda_{lm} + \mu_t + \varepsilon_{lmt} \tag{3.6}$$

Y_{lmt} corresponds to airline schedule behaviors of our interest, specifically, overall differentiation D, within-firm differentiation WD, between-firm differentiation BD and closest between-firm differentiation BD^{cls}. The regression of the overall differentiation D reflects the ex-post average response of the industry, with which we can hardly infer airlines' motivation behind such responses and differences between airlines. Our emphasis is laid on the regressions of within-firm and between-firm differentiation, as those are associated with two different aspects of airlines' motivation upon HSR competition.

The HSR impact is captured by the dummy variable HSR_{mt}, which takes the value of one if HSR presents in market m at time t, and zero otherwise. X_{it} denotes control variables including the airline market concentration measure HHI and the number of flights. HHI is calculated with flight frequency shares and controls for the intra-airline competition level. The market-level number of flights is included here to control for its impact on schedule distribution and, hence, differentiation, considering that intervals between adjacent flights tend to be smaller with a larger number of flights. More importantly, controlling for the number of flights eliminates the impact of HSR on departure time distribution through its impact on flight frequency, thus ensuring that the coefficient of HSR_{mt} we estimated is HSR's pure impact on departure time differentiation. In the within-firm differentiation model, the market-level number of flights is replaced by the focal airline's number of flights in the market. λ_{lm} represents airline-market fixed effect, capturing time-invariant airline-market specific characteristics and μ_t denotes time fixed effect.

HSR presence in China is widely considered exogenous to airline schedules(Wan et al., 2016; Zhang et al., 2017, 2018; Gu and Wan, 2020), because HSR openings are primarily aimed to boost economy and release rail capacity for cargo, thus independent from airline behaviors, especially its schedule design.

There are two considerations regarding HSR's impact on within-airline differentiation. First, improving service quality is one of the possible strategies airlines may consider under HSR's high competitive pressure. Given the number of flights per day, spreading departure times can attract more passengers with different preferences. This would generate a positive impact on the within-firm differentiation measure. However, if air travel demand is largely affected, airlines may have incentives to cluster flights to popular times, resulting in a reduction in within-airline differentiation. Combining the two considerations, we don't have an expectation on the sign of the coefficient. In terms of between-firm differentiation, theories in spatial product differentiation predict that when competition increases, firms might locate farther away from each other to avoid price competition or closer to "steal" customers. Thus, with the two opposite forces, we don't have a prediction on the sign of HSR coefficients on BD and BD^{cls}.

When discussing HSR's heterogeneous impacts on airlines, route distance is the aspect considered most by the researchers, for example, Wan et al. (2016) and Zhang et al. (2018). The literature generally finds that HSR is the most competitive on short-haul routes in terms of its impact on airfare, air traffic and/or capacity. From the perspective of airline schedule setting, route distance implies travel time and hence feasible operation period. As HSR takes an average of 10 hours on long-haul routes (>1200 km) in our sample, its departure time is impossible to be set in the evening except for overnight trains. Whereas, air transport is more flexible in setting schedules in the evenings. This yields airline's heterogeneous motivations and strategy pools in different markets. In the long-distance market, airlines may consider moving flights to evenings to take the competitive advantage. Whilst, in the distance market, this advantage vanishes and airlines are likely to be disadvantaged, especially for early morning and late evening flights, due to generally longer terminal access/egress and processing times.

The slot control status of an airport limits an airline's ability to freely set schedules, either moving towards or against competitors. Thus, airlines may react differently on various routes with or without slot-controlled airports. In China, slots in Beijing Capital International Airport (PEK), Shanghai Hongqiao International Airport (SHA), Shanghai Pudong International Airport (PVG) and Guangzhou Baiyun International Airport (CAN) are tightly controlled (Fu et al., 2015) and thus treated as slot-controlled airports in this study.

To identify the heterogeneous impact mentioned above, we estimate Eq.(3.6) with subsamples, specifically, long-haul routes, short-haul routes, slot-controlled routes and non-slot-controlled routes. The advantage of this method over the model with interactions is that observations share similar market characteristics in each subsample estimation.

3.2.3 Data and sample

This section introduces data sources, the formation of samples and descriptive statistics. Flight data for this study are collected from OAG Schedules Analyzer, which contains detailed flight planning information of all airlines in all air routes worldwide, such as operating airline, flight number, departure/arrival airport and time, effective (operation) period, the number of seats provided per flight, etc. HSR opening and service information are derived from the National Rail Timetable of China, a set of paper books published annually. Several editions are provided in some years to capture the massive evolution of train lines and schedule times. It can be the case that the information about a certain train service is not revealed immediately after its launch, so we double-check and revise HSR opening time from the news released by local governments and official media. Note that both the flight schedule data and train timetable data reveal planning information, and thus, we are not exposed to the information on ad-hoc real-life schedule changes due to unexpected demand and supply shocks.

We follow the definition of HSR by the International Union of Railways that the operating speed should be normally above 200 km/h (International Union of Railways, 2023). Thus, trains numbered starting with 'D' and 'G' in China are analyzed. Our data cover the years 2008 to 2015, during which HSR was introduced continuously.[5] The rail timetable books we refer to are mostly published in July, with some in other months from April to October. This allows us to focus on winter season of air transport which spans from November to March. As airlines make schedule plans beforehand, the launch of HSR is likely to have an immediate impact on the following season.

We focus on analyzing daily schedules of non-stop flights that connect airports in mainland China.[6] A Monday in the middle of each month in winter season of each year is picked as a representative day.[7] We define a market as a directional route consisting of the origin and destination airports. In order to investigate various strategies implemented by different airlines under different market conditions, we conduct the analysis based on airline-market-month combinations. Airlines under the same parent company are treated as the same one.

Air service provision in some thin markets is unstable, which may confound the identification due to market conditions and specific airline considerations unobservable to researchers. We first filter out the outlier-routes that have discontinuous operations in the fourty months we analyze. The observations with only one flight per day at market level are further dropped from the sample, since our main objective is to study flight departure time *distribution*. This procedure secures that at least two flights were operated in all sampled markets throughout the whole research period. Note we do not require the airline to have continuous operations in all months. Otherwise, only the big airlines in big markets are left in the sample, with which heterogeneity in HSR impacts across airlines and markets will be overlooked. The filtering process leads to an imbalanced panel sample with 13 airlines in 886 markets and a total of 91,100 observations.

[5]The first HSR was introduced in 2004 on the Qinhuangdao-Shenyang North route. After four years in 2008, another two lines Nanjing-Hefei and Beijing South-Tianjin opened, followed by rapid expansion during the later consecutive years.

[6]Connecting flights are rarely observed in China. A more common practice is direct flights with a stop in between the two endpoint airports with airplanes and crews not changed.

[7]See appendix B.1 for the list of days selected.

Table 3.3 summarizes the descriptive statistics of the main variables in our sample. The average within-airline differentiation and pooled between-airline differentiation are close in values, around 5-6 hours. Airlines are on average 2 hours away from their nearest competitors, reasonably significantly smaller than the pooled BD. We notice some airlines have flights departing at exactly the same time as their other flight or competitor's flight, making WD, BD or BD^{cls} reach as low as zero. For some of the cases where WD equals zero, the flights are in fact operated by different airlines, but under the same parent company and thus treated as one firm in this study.

Table 3.3: Summary Statistics

Variables	N	Mean	SD	Min	Max	#0s
D	91,100	313.0	106.6	0	720	46
WD	47,002	357.8	142.1	0	720	57
BD	87,985	306.6	103.9	0	720	36
BD^{cls}	87,985	120.7	131.9	0	720	780
nflight	91,100	2.284	2.033	1	24	0
Nflight	91,100	7.798	5.971	2	44	0
HSR	91,100	0.191	0.393	0	1	73,683
HHI	91,100	0.405	0.157	0.136	1	0

Notes: WD, BD and BD^{cls} requires the airline to have at least two flights and one competitor flight, respectively. Otherwise, these variables are set as missing value. Thus, the observation numbers of these variables are smaller than the sample size. nflight represents airline-level number of flights, and Nflight represents route-level (market-level) number of flights.

3.3 Results

3.3.1 Within-airline differentiation

As HSR presence is specific to the market, not the airline-market combination, we cluster the standard errors at the market level in all regressions. Table 3.4 shows estimation results on within-airline differentiation with different samples. Column (1) presents HSR impact in all selected markets and columns (2) to (9) present the impact on routes with different distances and slot-control status. To save space, we refer to slot-controlled routes as slot and non-slot-controlled routes as non-slot in the table. We do not find a statistically significant impact on within-airline differentiation with the full sample, but a negative one on short-haul routes (<1200 km) and non-slot-controlled routes. On average, airlines reduce departure time distances between their own flights by around 15 minutes after HSR entry in these markets. A statistically insignificant increase trend is found on the long-haul and slot-controlled routes, but the impact becomes statistically significant when the routes are both long-haul and slot-controlled.

Table 3.4: HSR effect on within-airline differentiation

DepVar:	Within-airline differentiation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
						>1200 km		<1200 km	
Sample:	Full sample	>1200 km	<1200 km	Slot	Non-slot	Slot	Non-slot	Slot	Non-slot
HSR	-5.688	4.782	-13.74**	3.315	-15.32**	10.91*	-0.680	-0.448	-22.17**
	(3.892)	(5.592)	(5.540)	(3.896)	(7.119)	(6.285)	(11.49)	(5.420)	(9.104)
Nflight [a]	-5.863***	-5.505***	-6.370***	-8.306***	-3.048	-9.032***	1.895	-7.277***	-4.884*
	(1.359)	(2.098)	(1.742)	(1.395)	(2.391)	(2.190)	(4.560)	(1.816)	(2.783)
HHI	-24.91**	-29.71	-19.90	2.491	-38.06***	-10.97	-39.06	10.90	-34.91**
	(11.82)	(19.31)	(14.80)	(20.81)	(14.20)	(32.20)	(23.62)	(27.23)	(17.40)
Airline-Route FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations [b]	47,002	17,279	29,723	21,127	25,875	9,391	7,888	11,736	17,987
R-squared	0.562	0.587	0.550	0.596	0.547	0.610	0.571	0.588	0.537

Notes: [a] Number of flights is at the airline-market-month level. [b] The number of observations is fewer than the full sample size, because not all airlines have *multiple* flights in our sample. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We interpret this effect by different levels of demand shock brought by HSR. When the demand shock is large, airlines tend to cluster flights at more popular departure times, while when the shock is moderate, airlines expand their flight intervals and thus increase product diversity to attract passengers.

On short-haul routes, as the literature points out, HSR poses a notable downward pressure on air travel demand. Consider demand variations throughout a day. The departure times with lower demand pre-HSR, which most probably are in the early morning or late evening, become more unattractive. This makes airlines suspend or move those flights to other popular times, making within-airline differentiation smaller. For the long-haul routes, on the one hand, they are not affected to a large extent. On the other hand, departure in the evening in long-haul market is infeasible for HSR except for a few overnight services but feasible for airlines. This means air transport on long-haul routes enjoys an extra advantage in the evening, apart from in-vehicle time advantage. In this sense, airlines would keep evening flights, so we don't find an obvious decreasing trend.

The rationale of demand shocks also applies to markets with different slot status. The slot-controlled routes connect China's four biggest airports, so they have high air travel demand. However, airlines may not supply enough flights to meet the demand because of insufficient slots. After HSR entry, as long as the air travel demand does not drop significantly below the supply, the incentives to change the departure distance of an airline's own flights would be low, considering the extra cost of obtaining or swapping slots. As a result, we don't see obvious changes in the within-airline differentiation on slot-controlled routes. Comparatively, without slot control, flight schedules can easily match the demand. When HSR brings a demand shock, airlines would justify the flight departure times to meet the new demand. We thus find a similar response on non-slot-controlled routes as that on short-haul routes.

The strategy of expanding flight intervals is only profitable in the market with moderate HSR impact and meanwhile with slot control status. With a large demand shock, increasing departure time diversity is not profitable, considering the low demand at some departure times. Similarly, in non-slot-controlled markets, this strategy tends to be less profitable because competitors can easily mimic the strategy, making it less effective in attracting passengers. Thus, we only find a positive effect on long-haul and slot-controlled routes.

We test the above rationale by two regressions (Table 3.5), with the airline's departure-time range and number of flights as dependent variables, keeping the main independent variables the same as in Eq.(3.6).[8] The departure-time range is calculated by the departure time of airline's last flight minus that of its first flight of a day and measured in minutes. The two regressions are estimated with the same subsamples as in columns (2) to (5) of Table 3.4. The result verifies our proposition. Airlines shorten their service range on short-haul routes and cut flights on both short-haul and non-slot-controlled routes.

Table 3.5: HSR effect on within-airline behaviors

DepVar:	Departure-time range				Number of flights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	>1200 km	<1200 km	Slot	Non-slot	>1200 km	<1200 km	Slot	Non-slot
HSR	7.379	-24.33***	-3.696	-12.03	-0.0835	-0.193***	-0.0113	-0.232***
	(8.419)	(7.306)	(6.465)	(8.810)	(0.0790)	(0.0701)	(0.0844)	(0.0567)
Nflight [a]	79.41***	76.18***	61.67***	95.06***				
	(6.216)	(3.554)	(3.590)	(5.295)				
HHI	-68.49***	-25.86	-63.59*	-40.49**	1.264***	0.385**	0.221	0.881***
	(24.34)	(18.88)	(32.41)	(16.93)	(0.241)	(0.164)	(0.330)	(0.130)
Airline-Route FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations [b]	17,279	29,723	21,127	25,875	17,279	29,723	21,127	25,875
R-squared	0.733	0.707	0.729	0.670	0.908	0.866	0.908	0.740

Notes: [a] Number of flights is at the airline-market-month level. [b] The number of observations is fewer than the full sample size, because not all airlines have *multiple* flights in our sample. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.3.2 Between-airline differentiation

Table 3.6 and Table 3.7 list estimation results of between-airline differentiation and closest between-airline differentiation, respectively. No noticeable effect is found on between-airline differentiation in all kinds of markets, while long-haul and slot-controlled routes witness an increase in closest between-airline distances. Specifically, airlines tend to move away from their nearest competitor by around ten minutes on average when HSR starts to serve those markets. The magnitude is economically non-negligible considering the average distance to the nearest rival's flight is 120 minutes. Comparing the coefficients in columns (5) to (9) of Table 3.7, only the long-haul and slot-controlled routes see a statistically significant positive

[8]The regression of daily flight frequency does not include itself as a regressor.

impact, suggesting that the results of column (2) and (4) are mainly contributed by the routes with both long distance and slot control status.

Table 3.6: HSR effect on between-airline differentiation

DepVar:	Between-airline differentiation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
						>1200 km		<1200 km	
Sample:	Full sample	>1200 km	<1200 km	Slot	Non-slot	Slot	Non-slot	Slot	Non-slot
HSR	-3.029	0.897	-4.980	1.928	-7.024	8.323	-10.36	0.304	-5.866
	(3.416)	(5.210)	(4.542)	(3.739)	(5.133)	(5.148)	(9.936)	(5.276)	(6.004)
Nflight [a]	-0.131	0.212	-0.284	-0.263	-0.0835	0.706	-0.267	-0.759	-0.0313
	(0.468)	(0.885)	(0.543)	(0.600)	(0.668)	(0.805)	(1.815)	(0.829)	(0.696)
HHI	8.908	18.62	4.170	14.89	4.523	60.30*	-4.251	-48.07	9.296
	(13.70)	(23.62)	(16.80)	(22.96)	(16.44)	(31.02)	(32.54)	(34.64)	(19.02)
Airline-Route FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations [b]	87,985	31,810	56,175	28,737	59,248	13,400	18,410	15,337	40,838
R-squared	0.444	0.462	0.433	0.517	0.427	0.547	0.440	0.493	0.421

Notes: [a] Number of flights is at the market-month level. [b] The number of observations is fewer than the full sample size, because not all markets have *multiple* airlines in our sample. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3.7: HSR effect on closest between-airline differentiation

DepVar:	Closest between-airline differentiation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
						>1200 km		<1200 km	
Sample:	Full sample	>1200 km	<1200 km	Slot	Non-slot	Slot	Non-slot	Slot	Non-slot
HSR	1.991	10.15**	-1.657	8.861**	-5.405	22.13***	-10.87	6.179	-3.556
	(3.345)	(4.877)	(4.453)	(3.698)	(4.825)	(5.391)	(9.140)	(5.424)	(5.751)
Nflight [a]	-9.875***	-8.731***	-10.09***	-6.925***	-12.06***	-4.098***	-14.57***	-8.190***	-11.16***
	(1.010)	(1.221)	(1.335)	(1.017)	(1.745)	(1.048)	(1.921)	(1.442)	(2.020)
HHI	230.5***	231.7***	229.6***	169.3***	235.9***	223.6***	215.0***	77.70**	244.9***
	(14.64)	(25.81)	(17.69)	(28.54)	(17.93)	(42.02)	(32.79)	(35.33)	(20.56)
Airline-Route FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations [b]	87,985	31,810	56,175	28,737	59,248	13,400	18,410	15,337	40,838
R-squared	0.569	0.580	0.564	0.676	0.520	0.657	0.529	0.695	0.517

Notes: [a] Number of flights is at the market-month level. [b] The number of observations is fewer than the full sample size, because not all markets have *multiple* airlines in our sample. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The reason why we do not find a statistically significant impact on the between-airline differentiation but do so on the closest between-airline differentiation is that when airlines move farther from their neighbor competitor, they are very likely getting closer to their far-away competitor at the same time. As the between-airline differentiation considers the airline's location relative to all competitors, the two opposite effects offset each other. This further demonstrates the need to study the closest between-airline differentiation.

We explain the above findings with airlines' ability to differentiate from competitors and the profitability of differentiation. Route distance implies the extent to which air travel demand is affected by HSR. On short-haul routes, where air travel demand saw a huge reduction, differentiation can not bring the desired outcome: reducing inter-airline competition and increasing fares because passengers may shift to HSR if airfares are higher. Therefore, we do not see a significant change in flight locations relative to competitors in these markets. However, on long-haul routes where the demand impact of HSR is mild, airlines can practice differentiation and may be better-off from price increases than doing nothing.[9] With a limited sample, we demonstrate that between-airline differentiation does increase airfares. See appendix B.2 for details.

The slot control status determines an airline's ability to locate flights freely. In non-slot-controlled airports, an airline's actions can be easily followed up by its competitors. Considering airlines' inclination to cluster flights in popular times discussed in section 3.3.1, it's hard for them to differentiate from each other. Meanwhile, demand shock is relatively large in those markets. Similar to short-haul routes, airlines may not gain from differentiation. In contrast, in slot-controlled markets, airlines have limited ability to change flight schedules unless swapping the affected flights with non-HSR flights. Differentiation is possible because not all airlines have enough slots to switch with.

Comparing the results in column (6) to column (9) of Table 3.7, only the market with both long distance and slot control status has a statistically significant positive impact. This means airlines would take the differentiation strategy only when the ability and profitability of differentiation exist simultaneously.

In determining airlines' ability to conduct differentiation, airline market share is also a key aspect. If an airline is seldom present in the market, its flights are surrounded by its competitors. This makes it hard for the airline to be away from competitors. In contrast, if the airline has a dominant market share, getting its flight farther away from others is relatively easy. To test this, we estimate the model with airlines with different market shares. In this regression, we consider only the markets with more

[9] Price increase is found on the routes where air-HSR has a large travel time difference (Gu and Wan, 2022).

than four flights per day to ensure that airlines with different market shares have distinct abilities of differentiation.[10]

We present the estimation results in Table 3.8. Three thresholds are employed to determine “dominant” airlines - 50%, 60%, and 70%. Statistically significant positive impacts are found for airlines with the larger route-level market share regardless of the threshold. The bigger the airline’s market share, the larger the effect. This result implicitly verifies that the ability to differentiate is crucial in airlines’ schedule design.

Table 3.8: HSR effect by airline market share

DepVar:	Closest Between-Airline Differentiation					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	$\geq$ 50%	<50%	$\geq$ 60%	<60%	$\geq$ 70%	<70%
HSR	12.04*	-0.439	26.40**	-0.0119	72.29***	0.810
	(6.415)	(1.702)	(10.61)	(1.672)	(26.23)	(1.710)
Nflight [a]	-7.142***	-4.728***	-10.17***	-4.724***	-5.031*	-4.884***
	(1.068)	(0.476)	(1.826)	(0.478)	(2.903)	(0.500)
HHI	433.8***	1.647	489.9***	18.69**	695.6***	59.81***
	(24.66)	(9.044)	(35.34)	(8.829)	(70.84)	(8.976)
Airline-route FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Observations	8,611	51,071	3,821	55,861	1,264	58,418
R-squared	0.715	0.522	0.706	0.527	0.677	0.553

Notes: [a] Number of flights is at the market-month level. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.3.3 Overall differentiation

Estimation results of the overall differentiation are listed in Table 3.9. The overall differentiation reflects the combination of within-airline and between-airline differentiation. In the short-haul and non-slot-controlled market, we find airlines, in general, tend to cluster flights when facing HSR competition, because the impact on

[10] In the market with fewer flights, airlines are able to easily differentiate from others even it has a small market share. For example, consider a market with two airlines operating one and two flights a day, thus accounting for 67% and 33% of the market, respectively. In this case, flights normally spread throughout the day, making it easy for the small airline to move away from the big airline further since the intervals between flights are large. In contrast, if there are 40 flights in the market, as on the Beijing-Shanghai route, a small airline can hardly find a departure time far from others.

within-firm differentiation outweighs that on between-firm differentiation. This result is in line with the literature that an increase in competition leads to a reduction in product differentiation (Borenstein and Netz, 1999; Salvanes et al., 2005). Recall the motivations discussed above. Our results imply that airlines have very limited ability and motivation to differentiate from competitors, while designing a schedule that catches most passengers' preference is more helpful in competition with HSR.

Table 3.9: HSR effect on overall differentiation

DepVar:	Overall differentiation				
	(1)	(2)	(3)	(4)	(5)
Sample:	Full sample	>1200 km	<1200 km	Slot	Non-slot
HSR	-4.486	1.751	-7.926*	3.261	-9.969**
	(3.221)	(4.975)	(4.247)	(3.545)	(4.860)
Nflight [a]	0.261	0.597	0.0823	0.176	0.382
	(0.461)	(0.887)	(0.531)	(0.588)	(0.658)
HHI	46.93***	33.94*	53.79***	83.21***	35.10***
	(11.26)	(19.38)	(13.75)	(20.38)	(13.31)
Airline-route FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	91,100	32,482	58,618	30,271	60,829
R-squared	0.458	0.476	0.447	0.553	0.431

Notes: [a] Number of flights is at the market-month level. Standard errors are clustered at the market level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.4 Conclusions

This study empirically investigates the impact of HSR entry in China on airline schedules and the heterogeneity of the impact. We adopt the concept of product differentiation to evaluate airline schedule distribution. Apart from the empirical literature focusing on the relationship between competition and the market's overall differentiation, the emphasis is placed on different types of differentiation, including within-firm and between-firm differentiation, aiming to figure out motivations for differentiation.

The results indicate that when airlines suffer from strong competition pressure, e.g., in short-haul markets, within-airline differentiation becomes smaller, explained by airlines' inclination to occupy the popular departure time slots. In comparison, if HSR brings mild competition, as on long-haul routes, airlines tend to employ a differentiation strategy. This may help them maintain or increase ticket prices. Another crucial prerequisite for conducting differentiation is the ability to secure a time slot far away from competitors. In slot-controlled airports where airlines have distinct slot resources, differentiating from others is possible. Hence, we observe an increase in the between-firm differentiation on the routes linking slot-control airports.

Our findings suggest that airlines may end up in a worse situation in the most affected markets, as there is no room for them to conduct differentiation strategies. Fierce inter-airline competition seems to be the only result. In contrast, airlines have a larger toolbox when dealing with mild HSR competition.

Chapter 4

Airport catchment expansion and competition

4.1 Introduction

Understanding an airport's catchment area is crucial for airports and airlines in making strategic operational decisions, particularly in multi-airport regions (MARs) where passengers can choose from multiple airports. The nationwide enhancement of transportation infrastructure, including HSR in China, is believed to expand the catchment areas of individual airports. However, these improvements also increase the range of airport choices available to passengers in surrounding areas, intensifying inter-airport competition. This dual effect raises questions about whether transport upgrades yield clear benefits for individual airports and the overall competitiveness of the national air transport system.

Literature on airport catchment areas often overlaps with airport-choice studies that examine specific MARs. These studies typically pre-determine the set of airports under consideration (see Zhang and Xie, 2005; Loo, 2008; Marcucci and Gatta, 2011; de Luca, 2012; Paliska et al., 2016; Stone, 2016, for example). The primary focus of these studies remains on examining the deterministic factors driving airport selection, rather than analyzing the evolution of an airport's catchment area itself.

Consequently, they cannot accommodate scenarios where an airport emerges as an additional alternative within the studied areas, thereby failing to capture the dynamic nature of airport catchment areas. Notable exceptions are Sun et al. (2017), Sun et al. (2021) and Wang et al. (2024), which identify MAR or airport catchment areas based on data. However, their emphasis lies in identifying and horizontally comparing the catchment areas rather than how ground transport infrastructure improvements affect these catchment areas.

Another prevalent characteristic in catchment literature is the simplistic definition of catchment areas, typically represented by concentric circles with arbitrary radii around each airport (e.g., Fuellhart, 2007; Marcucci and Gatta, 2011). This oversimplified method has notable limitations, as an airport's catchment area can significantly vary depending on factors like destination city, flight availability and frequency, and ticket prices (e.g., Lieshout, 2012; Gao, 2020). Failing to incorporate these related factors can result in a misleading and overly broad understanding of catchment areas.

Our study is also relevant to the extensive literature examining HSR's impact on aviation (see Zhang et al., 2019, for a recent review). While most studies focus on aspects such as airport passenger volume, airline service quality, traffic, capacity, and fares, few recognize HSR's role in expanding an airport's catchment area (e.g., Vespermann and Wald, 2011; Gu and Wan, 2020, 2022). In fact, this HSR-driven expansion is achieved by attracting passengers from more distant cities, suggesting that it is more accurate to view this as an extension of the airport's market reach. This reflects HSR's ability to draw passengers from a broader geographical area rather than ultimately enlarging the catchment area sizes, especially when considering induced inter-airport competition in the catchment area.

Upgraded transportation links, particularly HSR, can create network effects that impact all airports within a region, even those without HSR connections. While HSR extends the market reach of a specific airport, it simultaneously disadvantages other airports near this airport, leading to new competitive dynamics. Given the complexity of the HSR network in China, an airport may gain advantages on some routes while losing them on others. Consequently, a comprehensive investigation of HSR's net impact on all airports is essential.

This chapter develops a framework to evaluate the impact of HSR on airport catchment areas. We construct indicators and assess the HSR impact with a counterfactual-style analysis. Our methodology involves simulating total door-to-door travel time from the passenger's perspective, considering itinerary-level substitution among potential competing airports with detailed HSR and flight schedules. This approach allows our catchment measures to reflect not only the ground accessibility of each airport – as commonly used in the literature – but also their direct connectivity, including service availability (destination coverage), frequency, HSR-air schedule integration, and the population of catchment cities.

There are two key distinctions between our study and existing literature in defining airport catchment areas. First, our approach identifies competing airports from more distant regions, unlike traditional studies that focus on nearby airports. This is facilitated by HSR's advantages in medium-haul markets, which shorten the travel time between distant cities. As such, our method evaluates potential competition among all airports at the national level, not just those in close proximity.

Second, unlike traffic leakage studies that examine catchment areas by analyzing passengers near one airport choosing to depart from another (e.g., Fuellhart, 2007), we exclude local passengers from our catchment area measurements. Our analysis focuses exclusively on competition for non-local feeding passengers, deliberately disregarding traffic leakage effects. This approach implicitly assumes that intercity feeding HSR-air itinerary (where passengers take HSR trains to connecting airports) is insufficiently competitive with direct flights due to two considerations: the additional inconvenience involved, and significantly longer total travel times. The latter results because the time savings from HSR (compared to road transport) fail to compensate for the added schedule delays and transfer times between HSR stations and airports. As such, HSR feeding demonstrates no clear advantages over road-based alternatives and thus is not competitive compared with direct air services. Consequently, we posit that HSR has negligible impact on airport traffic leakage patterns. This justifies our exclusion of local passengers from consideration.

Based on the identified catchment for each air route, we then measure the competition intensity faced by each airport. Again, our measure is grounded in the substitution of itineraries within each passenger OD market. This method differs from Maertens (2012), who assesses airport competition based on catchment areas defined simply by geographical distance.

Our analysis reveals HSR's heterogeneous impacts on China's airport system. Airports possessing either high flight densities or extensive road-based feeding networks exhibit significant market reach expansion, resulting in measurable increases in their total catchment sizes. In contrast, smaller airports and those with limited road connectivity demonstrate the opposite effect, experiencing catchment area contraction. HSR's impact on airport competition intensity demonstrates relatively smaller heterogeneity, producing a system-wide modest increase. These results underscore the need for careful planning and evaluation of HSR-air integration projects by policymakers, as these projects may inadvertently lead to imbalanced development between primary and small airports and potentially worsen congestion at hub airports.

The rest of this chapter is structured as follows. Section 4.2 presents the data sources, explains the formation of our sample, and provides background information on intercity travel in China. Section 4.3 details our methodology for defining and measuring airport catchment areas and competition, as well as identifying HSR impact. Section 4.4 reports our key findings. Section 4.5 concludes the chapter and discusses policy implications.

4.2 Data

4.2.1 Data sources and sample formation

This study relies on two primary data sources. HSR schedules are obtained from China's National Rail Timetable, a yearly print publication.[1] Flight data comes from the OAG Schedules Analyzer, which provides global airline schedules, including carrier details, flight numbers, departure/arrival times, and operational periods. This allows us to determine the number of flights for each airport pair in a given year. Both datasets reflect planned schedules rather than real-time operations. Given our focus on airport-level catchment areas and competition dynamics over the years, this limitation does not significantly affect our analytical outcomes. In addition to the two data sources, we collect driving time between locations from Amap, while the population data of prefecture-level cities is obtained from the CEIC China Database.

We base our analysis on year 2015, when the HSR network was relatively established. Appendix C.1 lists number of city pairs served by HSR since it started to serve China market. A series of filtering processes are applied to airports. First, we exclude airports with unstable operations during the sample period, including those newly opened and suspended service. Next, we exclude airports in Hainan province as they are located on an isolated island, presenting additional geographical and psychological barriers for mainland passengers. As a result, we obtain a sample consisting of 174 airports.

4.2.2 Intercity travel in China

In China, airport density is relatively low compared to the United States.[2] Thus, people from many cities without airports (or with airports that have very limited destinations) must travel to another city to catch flights if they consider flying

[1]In some years, multiple editions are released to reflect significant changes in train lines and schedules.

[2]In 2015, there were over 500 airports providing passenger flights in US, compared to 206 airports in China. A straightforward calculation of airport density, considering both population and geographical area, reveals a ten-fold difference.

necessary, forming intercity feeding for air transport.[3] Otherwise, they can opt for conventional trains or road transport, which take considerably longer. Given the context, this study emphasizes intercity trips that require intermodal transportation. Thus, the passenger takes one HSR ride and one flight to complete the travel.[4]

Before the introduction of HSR, most connections to airports were probably made by road transport, such as private cars, inter-city coaches, or ride-hailing services. HSR makes such connections faster and easier, especially in cities where high-frequency trains are available. However, it is not as ideal as one might imagine. Unlike many European cities, rail stations and airports in China are not located nearby;[5] rather, there is a notable distance between the two. Thus, intuitively, HSR will primarily benefit passengers from cities located at an appropriate distance from the airport. This distance should enable HSR travel to outperform road transport in connecting passengers to airports when considering all associated travel times, including intracity travel between the HSR station and the airport, as well as the scheduling differences between the HSR journey and the flight. In contrast, passengers from cities near the airport may prefer road transport over HSR, potentially limiting their benefits from HSR services.

4.3 Methodology

In this section, we will define airport catchment areas and competition among airports. Specifically, we examine potentially competing itineraries within each OD passenger market and aggregate this itinerary-level information for each airport to derive the indicators that measure catchment areas and competition intensity at airport level. The impact of HSR is then assessed by comparing two scenarios: Sce-

[3] Sun et al. (2021) shows that half of the population can reach a HSR station within an hour of travel, while only a third can access an airport.

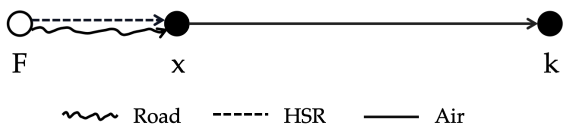
[4] It is possible that one passenger's origin and destination are both in hinterland cities. In this scenario, the passenger has to take two HSR rides and one flight, which makes the whole door-to-door travel time extremely long and consequently discourages this mode of travel. To simplify the analysis, this chapter will not consider this case.

[5] Exceptions include Shanghai Hongqiao Airport, Shijiazhuang Zhengding Airport and Chengdu Tianfu Airport, Beijing Daxing Airport, Haiou Meilan Airport, Zhengzhou Xinzheng Airport, Wuhan Tianhe Airport, and Tianjin Binhai Airport.

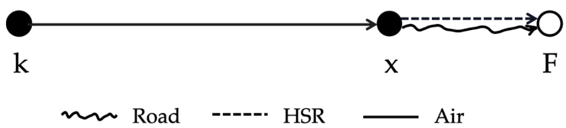
nario 1 considers only road transport in determining an airport's catchment area, while Scenario 2 incorporates both HSR and road transport.

4.3.1 Identification of feasible itineraries

This subsection defines what is a feasible itinerary. We focus on intercity feeding trips and examine the entire journey that a passenger undertakes from their origin to destination. Figure 4.1 illustrates this focal travel. We use capital letters to denote cities and lowercase letters to denote airports. Dashed lines represent HSR links, solid lines denote flights, and wavy lines indicate inter-city road transport. The whole travel involves a feeding leg, which connects passengers from the origin city F to the transfer airport x, and a flight leg from the transfer airport x to the destination airport k. The feeding leg may be completed by road transport or HSR, forming two types of feeding studied in this study: road feeding and HSR feeding. For road transport, we consider only private cars and non-scheduled services, such as taxi or ride-hailing. City F and airport k can interchange their roles as passengers' origin and destination, forming the F-x-k itinerary or the k-x-F itinerary. This is illustrated in Figures 4.1a and 4.1b, which we refer to as departure feeding or arrival feeding, respectively. We regard city F as the feeding city for air route xk under departure feeding, and for flight kx under arrival feeding.



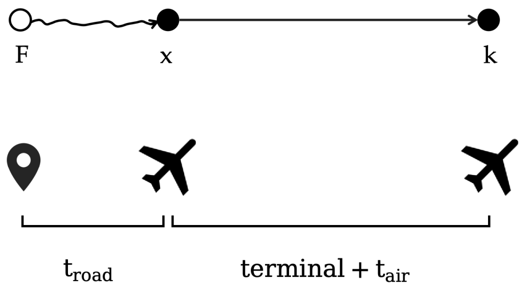
(a) Departure feeding



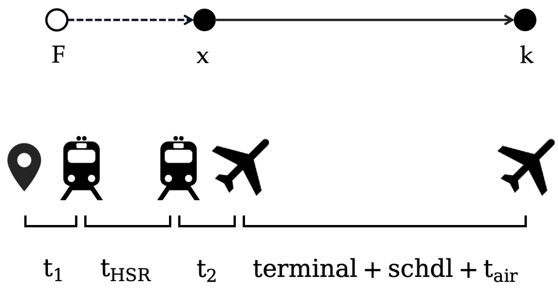
(b) Arrival feeding

Figure 4.1: Illustration of focal trip

Total travel time that a passenger may incur under the two types of feeding includes not only the in-vehicle time for both legs but also the transfer time. Figures 4.2a and 4.2b illustrate the decomposition of the total travel time for a passenger under the two types of feeding–road feeding and HSR feeding–respectively. To facilitate the demonstration, we show only the departure feeding case in the figure.



(a) Road feeding



(b) HSR feeding

Figure 4.2: Decomposition of total travel time

With road feeding, total travel time a passenger has to spend, T_R, is expressed as follows:

$$T_R = t_{road} + terminal + t_{air}, \tag{4.1}$$

where t_{road} represents driving time between the center of the origin city F and the airport x, *terminal* represents terminal time, including check-in, security check, and waiting at the gate before flight departure; t_{air} represents flying time. Note that *terminal* is a component depending on passengers' risk preferences. Passengers with risk-averse tendencies typically allocate more buffer time for airport arrivals, consequently experiencing longer *terminal* compared to risk-seeking passengers. Here it is given a value of 1 hour, which represents the minimum time required to handle all processes before flight departure. As such, we obtain the minimum total travel time for each itinerary with road feeding.

Total travel time with HSR feeding, T_H, is defined by the following equation:

$$T_H = t_1 + t_{HSR} + \underbrace{t_2 + terminal + schdl}_{schdiff} + t_{air}, \tag{4.2}$$

where t_1 represents driving time between the city center and the HSR station in the origin city F, t_{HSR} represents HSR in-vehicle time from feeding city F to the city where airport x is located, t_2 represents driving time between the HSR station and the airport in the city where airport x is located, *terminal* represents terminal time, which includes check-in, security checks, and waiting at the gate, *schdl* denotes schedule delay, which is added on top of the terminal time and due to the accommodation of the HSR and flight schedules and t_{air} represents flying time. Comparatively, there is no schedule delay in road feeding, as we consider only non-scheduled road transport. Note that t_2, *terminal* and *schdl* together account for the time difference between the HSR arrival and flight departure in the case of departure feeding, or between the flight arrival and HSR departure in the case of arrival feeding, denoted as $schdiff$. Thus, given a specific HSR train and flight pairing, we can compute the total travel time for each itinerary. Since multiple train and flight combinations may be available daily, a single itinerary can have multiple T_Hs. We select the minimum observed T_H to represent the itinerary's travel time, corresponding to the most efficient HSR-air connection. We omit the driving time between airport k and its city center from our analysis, as this time component applies uniformly across all itineraries and can thus be disregarded without loss of generality.

Building on these components of total travel time, we establish the following conditions to define a feasible itinerary. First, for both types of feeding, we exclude itineraries where direct flights exist between any airport in city F and airport k, as these would render intercity feeding comparatively disadvantageous in terms of both travel time and convenience. In such cases, HSR is unlikely to divert local passengers because – when accounting for the combined penalties of schedule delays and HSR station-airport transfer times – it fails to demonstrate sufficient advantage over road transport to alter passenger feeding patterns.

Next, we set conditions for the travel times associated with different segments of the entire trip. For both feeding types, the total time required to connect from city F to the transfer airport x must not exceed 5 hours. This threshold corresponds with the documented range of airport catchment areas in the literature, where spatial reach ranges from 75 miles to as much as 300 miles from the airport (Dresner et al., 1996; Suzuki and Audino, 2003; Suzuki et al., 2004; Fu and Kim, 2016; Ryerson and

Kim, 2018). Such variability stem from varying airport samples and whether fare differentials are considered. By adopting this relatively lenient time constraint, we intentionally accommodate potential price-induced variations in airport accessibility without explicitly modeling fare structures, thereby accommodating cases where competitive fares may extend effective catchment boundaries beyond typical ranges.

The total trip time with two types of feeding should not exceed either the driving time between the center of city F and the city where airport k is located, $road_{Fk}$ or the in-vehicle time of a direct HSR ride, HSR_{Fk}, if available. For HSR feeding, we add an extra criterion, which is the schedules of HSR and the flight should be somewhat "coordinated", so that passengers have adequate time to manage their transfer. Substracting the transfer time between HSR stations and airports, we assume the dwell time at airports, which is $terminal + schdl$ (or $schdiff - t_2$) should be in the range of $[1, 2]$ hours.

The preceding conditions yield the following system of inequalities. For any feasible itinerary with road feeding, we require:

$$\begin{cases} Fk \notin \mathcal{D}, \quad \mathcal{D} = \{\text{airport pairs served by direct flights}\} \\ t_{road} \leq 5 \\ T_R = t_{road} + 1 + t_{air} \leq road_{Fk} \\ T_R = t_{road} + 1 + t_{air} \leq HSR_{Fk}, \text{ if any} \end{cases} \tag{4.3}$$

Any feasible itinerary with HSR feeding should satisfy

$$\begin{cases} Fk \notin \mathcal{D}, \quad \mathcal{D} = \{\text{airport pairs served by direct flights}\} \\ t_1 + t_{HSR} + t_2 \leq 5 \\ T_H = t_1 + t_{HSR} + schdiff + t_{air} \leq road_{Fk} \\ T_H = t_1 + t_{HSR} + schdiff + t_{air} \leq HSR_{Fk}, \text{ if any} \\ terminal + schdl = schdiff - t_2 \in [1, 2] \end{cases} \tag{4.4}$$

4.3.2 OD-level rival airports and competition indicators

The above process identifies all feasible passenger OD pairs (Fk or kF) permitting intercity feeding via either road or HSR connections. For a given OD pair, multiple itineraries may exist, corresponding to different transfer airport options. We apply a competitiveness criterion by first calculating all possible total travel times and establishing the shortest duration as the benchmark. Any itinerary whose total travel time exceeds this benchmark by more than 30% is excluded from our analysis. This 30% tolerance threshold efficiently eliminates substantially slower options while retaining reasonably competitive alternatives that may offer other advantages (e.g., lower price).[6]

As such, we identify all competing itineraries within each OD market and establish airports as competitors if multiple transfer options exist for a given OD pair. Importantly, these competitive relationships are inherently OD-specific: two airports may compete for passengers traveling to certain destinations while remaining non-competitive for others. Figure 4.3 illustrates competing itineraries and the resulting OD level airport competition under road feeding. In the depicted scenario, airports x_1, x_2, and x_3 compete for passenger traffic in the Fk market. A key clarification: our definition of airport competition disregards airlines. That is, if two itineraries involving different transfer airports within the same OD market are operated by the same airline, we still consider this a competitive relationship. Conversely, different airlines operating identical air routes (same xk or kx pair) are treated as providing the same itinerary and thus not in competition. We denote the set of competing airports for market Fk (or kF) as $X(Fk)$ (or $X(kF)$), representing all viable transfer options for that specific OD pairing.

We quantify airport competition at the origin-destination (OD) market level by applying standard market concentration measures, treating each itinerary as a differentiated product. Our analysis employs: (1) the Herfindahl-Hirschman Index (HHI) computed from flight frequency shares of competing air routes, and (2) concentration ratios (either CR2 or CR4) measuring the combined market share of the

[6]We tried also 50% and 100% and the findings do not change qualitatively

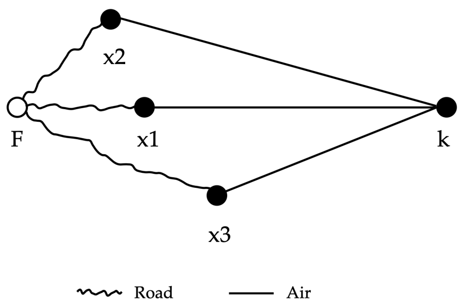


Figure 4.3: OD-level rival airports under road feeding

two and four largest itineraries, respectively. As these metrics all inversely represent competition intensity, higher values correspond to more concentrated markets and thus weaker competition.

4.3.3 Measuring catchment area and airport competition

Having identified all competing itineraries, we define city F as a feeding city for air route xk (or kx) if itinerary Fxk (or kxF) exists among the competing options. The set of all feeding cities for route xk is denoted as $N(xk)$, with $N(kx)$ defined analogously for the reverse direction. The complete set of feeding cities for airport x is then given by the union of all route-specific feeding sets: $N(x) = [\cup_k N(xk)] \cup [\cup_k N(kx)]$ for all valid airports k. By definition, a city is included in $N(x)$ if it serves as a feeding city for any route departing from or arriving at airport x. These feeding cities are then defined as airport x's catchment area.

We construct two complementary set of indicators to measure this catchment area. The first set of indicators capture the airport's geographical market reach. $NFeeding_x$ counts all potential feeding cities within the airport's catchment area, while $PopFeeding_x$ sums the total population across these feeding cities. Together, these metrics quantify the spatial extent of an airport's potential market, representing the theoretical maximum reach without considering the airport's market share in those areas. The second indicator, $Catchment_x$, measures the effective size of the catchment area by aggregating the population of each feeding city weighted by the airport's market share in that city. While $NFeeding_x$ and $PopFeeding_x$ reflect the breadth of market coverage, $Catchment_x$ quantifies the actual accessible demand based on the airport's competitive position in each market segment. Below we detail the construction of these two indicators.

Market reach. The two indicators are constructed specifically by:

$$NFeeding_x = |N(x)| \tag{4.5}$$

$$PopFeeding_x = \sum_{F \in N(x)} pop_F \tag{4.6}$$

where pop_F represents population of city F. The union-based construction of these two indicators establishes them as theoretical maximums for an airport's market potential.

We further classify the feeding city set $N(x)$ into two distinct categories: exclusive feeding cities and shared feeding cities, and then calculate the feeding city count and population in the corresponding categories. Exclusive feeding cities are those appear only in $N(x)$ and in no other airport's feeding set, while shared feeding cities comprise all remaining cities in $N(x)$ that appear in at least one other airport's feeding set. This exclusive versus shared distinction provides dual insights: it reflects both the market power of an airport in its unique areas and the intensity of competition it faces. Specifically, a higher proportion of exclusive cities suggests greater market power applies in more regions, while an increasing proportion of shared feeding cities indicates greater geographic overlap with competitor airports, revealing more extensive competition for passenger demand across overlapping regions.

Market share-adjusted catchment. For each feeding city, we calculate the proportion of itineraries that include airport x and treat this share as airport x's market share in that city. The airport's catchment contribution from each feeding city is then calculated as the product of (1) this market share and (2) the city's population. The total catchment size, $Catchment_x$, is obtained by aggregating these contributions across all feeding cities in $N(x)$. Specifically, it is calculated as follows:

$$Catchment_x = \sum_{F \in N(x)} pop_F \times s_{x,F} \tag{4.7}$$

where $s_{x,F}$ is the market share of airport x in city F, calculated as:

$$s_{x,F} = \frac{\text{Number of itineraries through } x \text{ from/to } F}{\text{Total itineraries from/to } F} \tag{4.8}$$

In this way, the population-adjusted catchment captures the dual effects of HSR services. First, it reflects the potential market expansion effect: as HSR extends an airport's geographical reach, the set of feeding cities $N(x)$ may grow, potentially increasing $Catchment_x$. Second, it incorporates the competition effect: when multiple airports serve the same OD markets, the focal airport's market share ($s_{x,F}$) in affected feeding cities may decrease, thereby reducing its overall catchment size. These countervailing forces - market expansion versus share dilution - collectively determine the net impact of HSR on an airport's accessible demand.

Competition. We formally define airport x's competition intensity ($AirComp_x$) through a two-stage weighted aggregation process for departure and arrival feeding separately. First, itinerary-level competition measures (HHI, CR2 and CR4 defined in Section 4.3.2) are aggregated to the route level, weighted by the population of feeding cities to emphasize bigger cities. For airport x under departure feeding on route xk, the competition intensity is given by:

$$AirComp_{xk} = \frac{\sum_{F \in N(xk)} \alpha_{Fk} \times pop_F}{\sum_{F \in N(xk)} pop_F} \tag{4.9}$$

where α_{Fk} captures competition intensity for itinerary Fxk. Similarly, for airport x under arrival feeding on route kx:

$$AirComp_{kx} = \frac{\sum_{F \in N(kx)} \alpha_{kF} \times pop_F}{\sum_{F \in N(kx)} pop_F} \tag{4.10}$$

where α_{kF} represents competition in itinerary kxF, reflected by the value of HHI, CR2 and CR4. These population weights ensure larger feeding markets contribute more significantly to route-level competition measures.

Second, these route-level measures are aggregated to the airport level using annual flight frequencies as weights, giving greater importance to heavily trafficked routes. The competition intensity airport x faces under departure feeding combines all outbound routes:

$$AirComp_x^{dep} = \frac{\sum_{k \in K_{x\cdot}} AirComp_{xk} \times freq_{xk}}{\sum_{k \in K_{x\cdot}} freq_{xk}} \tag{4.11}$$

while arrival competition intensity combines all inbound routes:

$$AirComp_x^{arr} = \frac{\sum_{k \in K_{\cdot x}} AirComp_{kx} \times freq_{kx}}{\sum_{k \in K_{\cdot x}} freq_{kx}} \tag{4.12}$$

Here $freq_{xk}$ and $freq_{kx}$ represent annual frequencies, with $K_{x\cdot}$ and $K_{\cdot x}$ denoting set of destination airports from x and set of origin airports to x respectively. The final airport-level competition intensity is obtained by taking the mean of the departure and arrival components:

$$AirComp_x = \frac{1}{2}(AirComp_x^{dep} + AirComp_x^{arr}) \tag{4.13}$$

This comprehensive metric captures three fundamental dimensions of airport competition through its hierarchical construction. First, the concentration of competing itineraries within each origin-destination market is quantified through the α terms, reflecting market-specific competitive pressures. Second, the relative importance of different feeding markets is incorporated through population weighting, where larger cities (higher pop_F) contribute more significantly to the route-level competition measures. Formally, this means that for any two feeding cities F_1 and F_2 where $pop_{F_1} > pop_{F_2}$, itinerary F_1xk receives greater weight than F_2xk when calculating route xk's competition intensity ($AirComp_{xk}$).

Third, the operational intensity of routes is accounted for through frequency weighting at the airport-level aggregation. Routes with higher annual frequencies ($freq_{xk}$ or $freq_{kx}$) exert proportionally greater influence on the final competition measures

($AirComp_x^{dep}$ and $AirComp_x^{arr}$). This three-dimensional approach ensures the metric reflects both the geographic and operational realities of airport competition, ensuring that $AirComp_x$ provides consistent and meaningful comparisons across airports of different sizes and network configurations.

4.3.4 HSR impact

We assess HSR's impact through a counterfactual-style analysis comparing two transportation scenarios: (1) a road-only baseline considering solely road-accessible feeding itineraries, and (2) a comprehensive road+HSR scenario incorporating both road and HSR connections. This analytical framework isolates the exogenous effects of HSR infrastructure by holding airline operations constant, thereby capturing HSR's pure network impact on airport connectivity and competition prior to any strategic responses from airlines or airports.

We quantify HSR's effects by comparing our constructed metrics between these scenarios, while also examining heterogeneous effects across airport size categories. Airports are stratified into size groups based on passenger volume percentiles: those below the first quartile (small airports) and those above the third quartile (large airports).

Specifically, the absolute impact of HSR services is quantified as:

$$\Delta\gamma_x = \gamma_{x,2} - \gamma_{x,1} \tag{4.14}$$

where $_{x,1}$ represents any of our established metrics ($NFeeding_x$, $Catchment_x$, and $Aircomp_x$) under the road-only scenario, and $_{x,2}$ represents the corresponding metric under the combined road-HSR scenario. The relative percentage change is calculated as:

$$\Delta\%\gamma_x = \frac{\gamma_{x,2} - \gamma_{x,1}}{\gamma_{x,1}} \times 100\% \tag{4.15}$$

The directional changes in our core metrics reveal distinct aspects of HSR's influence on airport competitiveness. A positive $\Delta NFeeding_x$ (and corresponding

$\Delta\% NFeeding_x$) indicates geographic market expansion, demonstrating how HSR connectivity enables the airport to access new feeding cities beyond its original road-based catchment area. This expansion effect occurs when HSR extends the airport's effective service radius by improving surface access to previously disconnected regions. Conversely, negative values of $\Delta AirComp_x$ (and $\Delta\% AirComp_x$) reflect intensified competitive pressure, emerging when HSR services provide passengers in catchment areas with improved access to alternative airports, thereby reducing the focal airport's market dominance.

The net impact captured by $\Delta Catchment_x$ (and $\Delta\% Catchment_x$) represents the balance between these opposing forces - the positive expansion effect from increased $NFeeding_x$ and the negative competition effect from reduced market shares. This metric yields important policy implications through their sign and magnitude. A significantly positive $\Delta Catchment_x$ indicates that HSR integration predominantly expands the airport's market reach, suggesting the infrastructure serves as a complement that enhances the airport's accessibility and passenger base. This scenario typically benefits the airport through increased demand potential. In contrast, a negative $\Delta Catchment_x$ reveals that competitive pressures outweigh market expansion, particularly when accompanied by substantial negative $\Delta AirComp_x$ values, positioning HSR as a helper that diminishes the airport's market position. In such cases, the airport may face strategic challenges in maintaining its competitive standing. When $\Delta Catchment_x$ approaches zero, it implies the expansion and competition effects are roughly offsetting each other, resulting in minimal net change to the airport's overall catchment strength.

4.4 Results

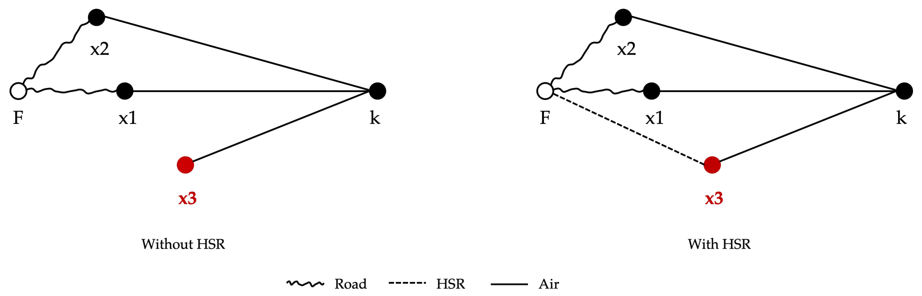
4.4.1 Sample composition and itinerary-level results

Our analysis examines 174 Chinese airports using 2015 operational data. Among all airports, 27 (representing 15.5% of the total) demonstrated no viable feeding city connections even under the road-only baseline scenario. Importantly, this does not reflect geographic isolation - these airports are physically proximate to cities - but rather indicates their inability to competitively attract intercity feeding passengers in any OD markets. This leaves 147 airports with established catchment areas for which we calculated all metrics under both transportation scenarios.

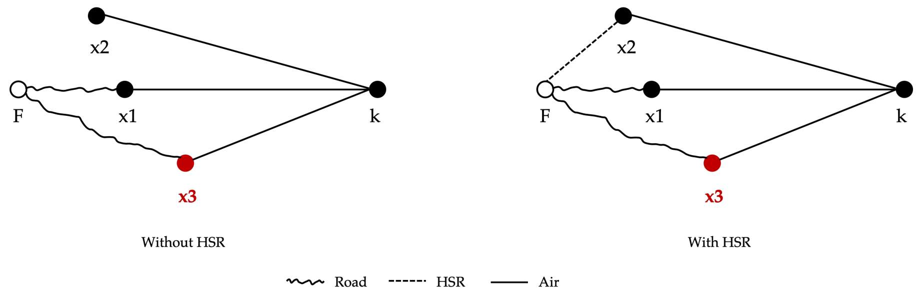
HSR influences an airport's competitiveness through two mechanisms. The first mechanism involves an proactive expansion, whereby HSR provides direct connections between the focal airport and additional feeding cities. This creates new competing itineraries where the focal airport gains access to previously untapped markets through improved HSR connectivity. Such expansion enables airports to actively penetrate new markets. Importantly, if these newly accessible markets are more competitive than the airport's existing market, this expansion can lead to an increase in the airport's overall competition intensity. The second mechanism involves airport's passive market share erosion, where HSR strengthens rival airports by enhancing their accessibility. As such, rival airports capture portions of the focal airport's existing market share, leading to an increase in the overall competition intensity of the focal airport.

Figure 4.4 illustrates the dual mechanisms of HSR impact on airport competitiveness, using airport $x3$ as our focal case. In Figure 4.4a, we demonstrate the active expansion mechanism. Prior to HSR introduction, the Fk market was served only by airports $x1$ and $x2$. With new HSR connections between city F and $x3$'s location, $x3$ becomes a viable third option, proactively expanding its market reach through HSR connections. Figure 4.4b shows passive market erosion. While $x3$'s HSR connectivity remains unchanged, competitor $x2$ gains HSR access to city F. This transforms $x2$ from an irrelevant to a competing airport in the Fk market. From $x3$'s perspective, its market share is passively eroded by this new rival airport.

Among the 147 airports with established catchment areas, 35 airports (23.8% of the 147) exhibited zero HSR exposure, experiencing neither direct HSR connections nor competitive effects from HSR-linked rival airports. These unexposed airports are excluded from our counterfactual-style analysis for HSR impact. Our HSR impact



(a) Proactive



(b) Passive

Figure 4.4: Illustration of competition increase source

assessment thus focuses on these 112 HSR-exposed airports.

For the OD markets within each HSR-exposed airport, the majority (87%) show no change in competition intensity. A small but meaningful share experience measurable effects: 8% of markets undergo passive market share erosion due to strengthened competitor airports, while 5% proactively expand their market coverage enabled by new HSR-linked feeding cities. This distribution highlights that while HSR exposure is widespread (affecting 76.2% of airports), its competitive effects remain concentrated in specific markets.

Table 4.1 presents the counts of itineraries and OD markets under both scenarios. Our analysis identifies 97,936 feasible itineraries in road-only baseline scenario and 118,268 in road+HSR scenario, with 35.5% and 40.2% of them respectively exceeding the 130% travel time tolerance threshold relative to the fastest option in each OD market. After applying this competitive threshold, our final analysis sample contains 63,139 itineraries (Road-only scenario) and 70,625 itineraries (Road+HSR scenario), representing 40,193 and 43,508 unique OD markets respectively. The increased counts in Road+HSR scenario reflect the expanded connectivity options introduced by HSR services. Importantly, it creates 8.1% more OD markets compared to the baseline scenario.

Table 4.1: Itineraries and OD markets under two scenarios

Variables	Road feeding	Road+HSR feeding	Δ%
Feasible itineraries count	97,936	118,268	20.7%
Competing itineraries count	63,139	70,625	11.8%
OD markets count	40,193	43,508	8.2%

Note: Feasible itineraries are those that meet all connection requirements defined in Section 4.3.1. Competing itineraries are a subset of feasible ones with total travel time $\leq$ 130% of the shortest OD-market travel time as defined in Section 4.3.2.

Table 4.2 compares OD market characteristics between road-only and road+HSR scenarios, reporting average travel times, alternative airport counts, and the absolute/relative differences between scenarios. We report two sets of differences for average total travel time, one excluding newly accessible OD markets and the other including them. The first set evaluates whether HSR reduces travel time in markets that are already served by road connections, while the second assesses the improvement by comparing travel times to hypothetical road-based travel in newly accessible markets. Since it is not meaningful to analyze the number of alternative airports in non-existing markets, we report only the differences excluding new ODs for the number of alternative airports.

For markets existing in both scenarios, results show a slight increase in average travel times under HSR integration (Δ = 0.007 hours, Δ% = 0.16%), reflecting minor connectivity improvements in terms of travel time. When considering newly accessible OD markets enabled by HSR (absent in the road-only scenario), travel time reductions remain modest (Δ = -0.119 hours, around 7 minutes, Δ% = -1.16%).

The availability of alternative airports varies significantly across OD markets. While over 50% of markets function as monopolies, some routes demonstrate remarkable competition. A striking example is the Huangshan-Shenyang market, which offers passengers up to 11 transfer options, including two Shanghai airports (SHA and PVG) along with airports in Nanjing, Hangzhou, Ningbo, Hefei, Nanchang, Changzhou, Jinhua, Wuxi, and Yangzhou.

Table 4.2: Selected statistics at OD market level

Variables	N	Mean	Sd	Min	P25	P50	P75	Max
Average total travel time								
Road-only scenario	40,193	5.061	1.490	1.075	3.922	4.990	6.116	10.71
Road+HSR scenario	43,508	5.213	1.583	1.075	4.003	5.115	6.311	11.94
Δ, new ODs excluded	40,193	0.007	0.170	-2.430	0	0	0	2.213
Δ%, new ODs excluded	40,193	0.16%	2.92%	-29.5%	0	0	0	29.2%
Δ, new ODs included	43,508	-0.119	0.584	-5.625	-2e-08	0	0	2.246
Δ%, new ODs included	43,508	-1.16%	6.47%	-49.3%	-5e-07%	0	0	42.1%
Number of alternative airports								
Road-only scenario	40,193	1.571	0.924	1	1	1	2	11
Road+HSR scenario	43,508	1.623	0.987	1	1	1	2	11
Δ, new ODs excluded	40,193	0.082	0.366	0	0	0	0	6
Δ%, new ODs excluded	40,193	5.88%	27.1%	0	0	0	0	600%

Notes: Observation unit:(directional) OD market. Δ represents the absolute difference in the corresponding metrics between road-only baseline scenario and road+HSR scenario, while Δ% represents the relative difference (percentage change) between the two scenarios.

Although the system-wide average of alternative airports shows only a marginal increase from 1.57 to 1.62, this aggregate effect masks significant heterogeneity across airports. The 5.88% average relative increase is driven primarily by 5,800 markets (13.3% of 43,508), where the number of alternative airports increased by 1.33 on average (95% increase from baseline). In contrast, the vast majority of markets (86.7%) show absolutely no change in competitor counts, reflecting either lack of HSR connectivity or insufficient HSR quality to alter airport choice calculus.

The analysis reveals a fundamental dichotomy in HSR's impacts. For the vast majority of existing origin-destination (OD) markets, road connections prove sufficiently robust that HSR introduction yields no measurable competitive effect - neither increasing alternative airport options nor significantly decreasing travel times. This suggests that conventional road networks already provide adequate airport accessibility for most routes. However, for a small group of routes, HSR makes a big difference by nearly doubling the number of airport options available to travelers.

4.4.2 Airport's market reach

Table 4.3 shows how airports' market reach differs between the road-only and road+HSR scenarios. The average number of feeding cities per airport increases from 13 (road-only) to 16 (road+HSR), representing an average 18.7% expansion in geographical connectivity. However, the benefits concentrate almost entirely among the top 25% airports – those with the best existing road connectivity and highest flight volumes. This implies a correlation between road and HSR infrastructure: regions with strong road networks gain HSR access, while underserved areas fall further behind, widening existing connectivity disparities.

Table 4.3: Results for airport market reach

Variables	N	Mean	Sd	Min	P25	P50	P75	Max
Road-only scenario								
NFeeding	147	12.97	9.836	1	5	11	19	45
Share of exclusive	147	13.5%	21.5%	0%	0%	4.76%	20.0%	100%
Share of shared	147	86.5%	21.5%	0%%	80.0%	95.2%	100%	100%
PopFeeding('000)	147	56,086	54,342	272	12,011	37,886	88,345	232,310
Share of exclusive	147	2.99%	14.6%	0%	0%	0%	0%	100%
Share of shared	147	97.0%	14.6%	0%	100%	100%	100%	100%
Road+HSR scenario								
NFeeding	147	15.78	14.10	1	5	11	22	67
Share of exclusive	147	13.4%	21.3%	0%	0%	5.6%	18.2%	100%
Share of shared	147	86.6%	21.3%	0%	81.8%	94.4%	100%	100%
PopFeeding('000)	147	71,160	78,954	402	12,011	40,094	93,892	343,776
Share of exclusive	147	2.05%	12.4%	0%	0%	0%	0%	100%
Share of shared	147	98.0%	12.4%	0%	100%	100%	100%	100%
HSR impact								
ΔNFeeding	112	3.679	6.184	0	0	0	5	29
Small airports	28	0.357	0.870	0	0	0	0	3
Big airports	28	10.07	7.925	0	2.50	9.50	16.50	29
Δ%NFeeding	112	18.7%	27.5%	0%	0%	0%	28.3%	100%
Small airports	28	5.88%	19.6%	0%	0%	0%	0%	100%
Big airports	28	45.6%	27.7%	0%	21.9%	49.6%	72.3%	87.5%
ΔPopFeeding('000)	112	19,785	35,190	0	0	0	25,431	158,937
Small airports	28	1,258	3,508	0	0	0	0	16,738
Big airports	28	53,986	46,191	0	14,007	42,809	91,614	158,937
Δ%PopFeeding	112	23.1%	40.0%	0%	0%	0%	36.1%	227.1%
Small airports	28	7.90%	32.5%	0%	0%	0%	0%	172.4%
Big airports	28	54.0%	39.4%	0%	22.8%	53.9%	74.8%	144.6%

Notes: Small airports: $\leq$ 25th percentile of annual flight volume; Large airports: $\geq$75th percentile.

Maximum feeding city counts reach remarkably high levels – with individual airports serving 45 feeding cities in the road-only scenario compared to 67 when HSR is available. These peak values correspond to Hefei Xinqiao International Airport and Wuhan Tianhe International Airport respectively, both benefiting from their central geographical locations within China's transportation network.

Our population-based measure $PopFeeding_x$ generates substantial absolute values (averaging 56-71 million people under the two scenarios), yet displays patterns consistent with $NFeeding_x$. A distinction emerges when examining feeding city types: while exclusive cities (served by only one airport) account for 13.5% of all feeding cities, they represent just 2–3% of the total catchment population. This contrast suggests that these exclusive cities are predominantly smaller areas.

We visualize the spatial distribution of both baseline airport metrics (road-only scenario) and HSR-induced changes through a bubble plot. Each airport's road-only values are encoded in bubble sizes, where larger diameters correspond to greater magnitudes. Color gradient indicates the direction and degree of HSR impact, where blue tones indicate positive changes (catchment area expansions) and orange tones represent negative changes. This combined representation allows for immediate visual comparison of pre-existing airport characteristics and their HSR-induced modifications across geographic space.

Figure 4.5 shows the bubble plot of $NFeeding_x$. The results reveal a distinct spatial pattern: major airports located at the core of China's HSR network – including Beijing Capital (PEK), Shanghai Pudong (PVG) and Hongqiao (SHA), Wuhan (WUH), and Changsha (CSX) – exhibit the most substantial market reach expansion. These airports, which already possessed extensive road-based feeding networks, benefit disproportionately from their central positions in the HSR system, gaining the highest number of additional connections. In contrast, peripheral airports with limited initial feeding networks show minimal improvements in market reach, demonstrating that HSR connectivity tends to reinforce rather than mitigate existing spatial inequalities in China's air transport system.

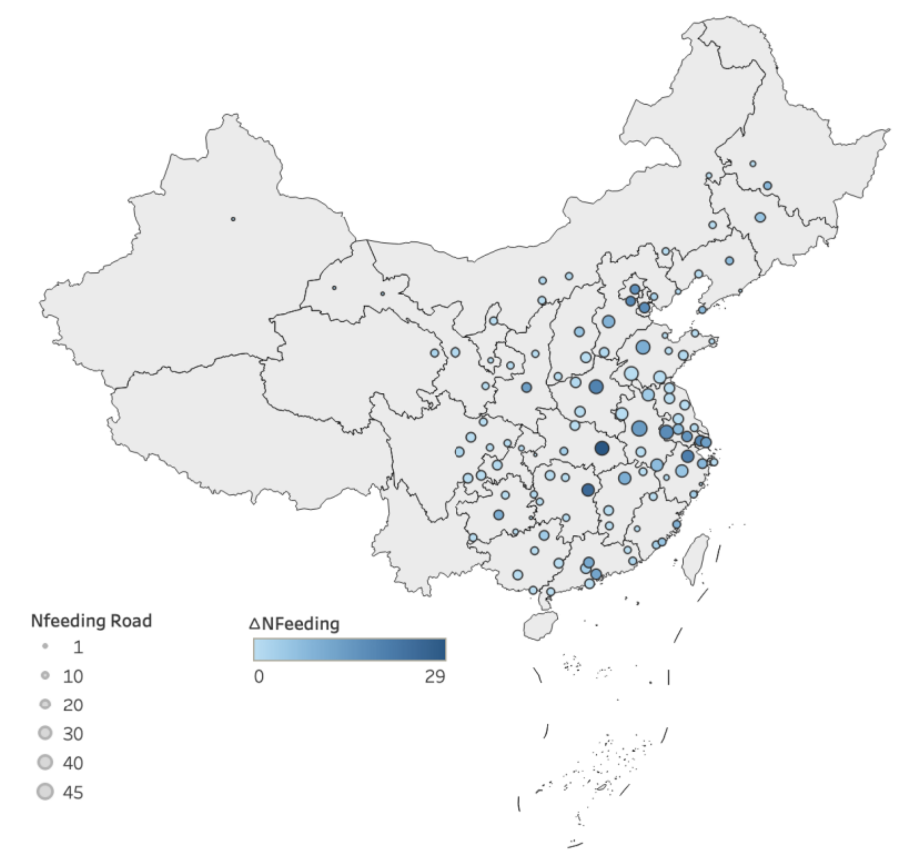


Figure 4.5: Spatial distribution of airport market reach

4.4.3 Airport competition

Table 4.4 presents descriptive statistics that compare airport competition between the road-only and road+HSR scenarios, quantifying the incremental impact of HSR connectivity. Note that as competition intensity is measured by market concentration, larger bubbles indicate lower numerical values i.e., lower concentration, but higher actual competition intensity. Blue tones indicate increased competition increase, while orange tones mark competition decrease.

The indicators reveal relatively low competition among Chinese airports, with an average HHI exceeding 0.6 and a two-firm concentration ratio exceeding 0.9 under both scenarios.

Compared to market reach metrics, HSR's impact on airport competition shows less heterogeneity. Most airports experience an increase in competition intensity,

Table 4.4: Results for airport competition

Variables	N	Mean	Sd	Min	P25	P50	P75	Max
Road-only scenario								
AirComp(HHI)	147	0.657	0.145	0.396	0.546	0.642	0.747	1
AirComp(CR2)	147	0.931	0.055	0.752	0.896	0.938	0.977	1
AirComp(CR4)	147	0.993	0.010	0.949	0.991	0.998	1	1
Road+HSR scenario								
AirComp(HHI)	147	0.643	0.145	0.391	0.541	0.617	0.711	1
AirComp(CR2)	147	0.925	0.056	0.749	0.889	0.931	0.973	1
AirComp(CR4)	147	0.992	0.011	0.947	0.990	0.996	1	1
HSR impact								
ΔAirComp(HHI)	112	-0.019	0.040	-0.341	-0.025	-0.007	-5e-05	0.068
Small airports	28	-0.027	0.066	-0.341	-0.030	-0.008	0	0.022
Big airports	28	-0.026	0.036	-0.142	-0.030	-0.015	-0.005	0.027
Δ%AirComp(HHI)	112	-2.71%	5.34%	-39.93%	-3.96%	-1.18%	-0.00%	11.76%
Small airports	28	-3.72%	8.10%	-39.93%	-4.55%	-1.08%	0%	5.18%
Big airports	28	-3.72%	4.95%	-20.50%	-4.46%	-1.94%	-0.80%	4.13%
ΔAirComp(CR2)	112	-0.007	0.015	-0.109	-0.009	-0.002	0	0.033
Small airports	28	-0.011	0.024	-0.109	-0.012	-0.002	0	0.003
Big airports	28	-0.009	0.010	-0.034	-0.012	-0.007	-0.001	0.006
Δ%AirComp(CR2)	112	-0.79%	1.61%	-11.06%	-1.00%	-0.24%	0%	3.81%
Small airports	28	-1.17%	2.45%	-11.06%	-1.35%	-0.18%	0%	0.39%
Big airports	28	-0.93%	1.06%	-3.41%	-1.32%	-0.79%	-0.09%	0.66%
ΔAirComp(CR4)	112	-0.001	0.002	-0.019	-0.002	-0.0002	0	0.002
Small airports	28	-0.001	0.001	-0.005	-0.001	0	0	0.0008
Big airports	28	-0.001	0.001	-0.003	-0.002	-0.001	-0.0001	0.0004
Δ%AirComp(CR4)	112	-0.11%	0.22%	-1.86%	-0.15%	-0.02%	0%	0.23%
Small airports	28	-0.07%	0.14%	-0.54%	-0.09%	0%	0%	0.08%
Big airports	28	-0.13%	0.12%	-0.33%	-0.20%	-0.13%	-0.01%	0.04%

Notes: Small airports: ≤ 25th percentile of annual flight volume; Large airports: ≥75th percentile.

but the system-wide impact remains modest. The system-wide average impact on metrics with HHI amounts to just 2.7%, with even more limited effects on market concentration ratios – both the CR2 and CR4 indices show minimal changes. This suggests that HSR connectivity has particularly weak influence on the dominance of major players in each OD markets.

Notably, while the average HSR impact does not differ significantly between small and large airports – a result potentially attributable to our competition measure's uniform value of all airports within each OD market – small airports exhibit greater variation in their HSR impact (higher standard deviation). This indicates that smaller airports demonstrate more heterogeneous HSR effects, likely due to their uneven exposures to HSR.

Figure 4.6 presents the spatial distribution of our airport competition measure ($AirComp$) derived from HHI calculations. The visualization reveals that centrally located airports in China tend to experience the most substantial competition intensification following HSR introduction. Notably, these airports initially exhibited relatively low competition levels in the road-only scenario (with relatively smaller bubbles). Conversely, airports with higher baseline competition show more modest increases. This pattern suggests HSR, to some extent, reduces competition disparities across China's airport network.

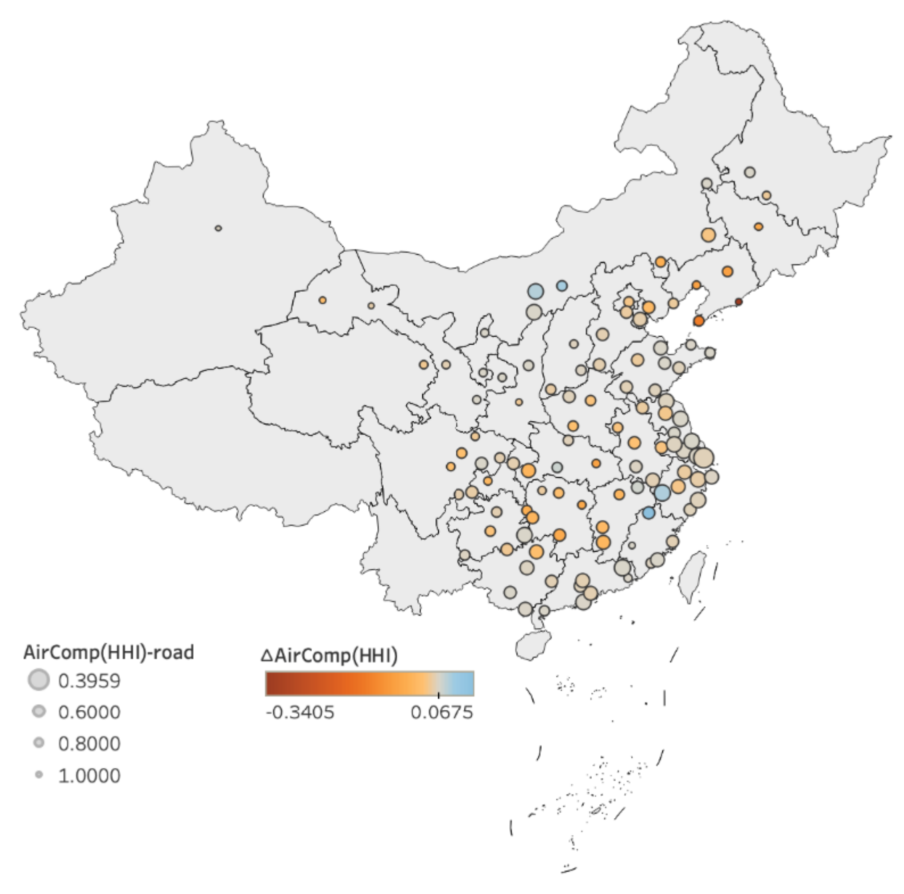


Figure 4.6: Spatial distribution of airport competition

4.4.4 Catchment area size

Table 4.5 reports comparisons of the metric for airport catchment size between the two scenarios. After accounting for competition in overlapping catchment areas, airports can potentially attract an average of 9 million external passengers (excluding local populations), though with considerable variation (high standard deviation). This market share-adjusted catchment measure is substantially smaller than the $PopFeeding_x$ values (56-71 million) reported in Table 4.3, highlighting the critical importance of incorporating competition effects when evaluating airport catchment areas.

HSR yields net +0.15 million absolute catchment growth but an overall negative relative difference (-12.61% for Δ%). The values at quartiles reveal that this contradiction stems from highly concentrated benefits - a small number of airports account for the positive aggregate change through substantial individual gains, while most airports experience catchment size reductions. The table further indicates that large airports tend to be the primary beneficiaries of HSR connections.

Table 4.5: Results for catchment area size

Variables	N	Mean	Sd	Min	P25	P50	P75	Max
Road-only scenario								
Catchment('000)	147	8,985	17,250	0.004	279	1,143	6,613	98,457
Road+HSR scenario								
Catchment('000)	147	9,095	18,865	0.004	169	938	5,428	115,030
HSR impact								
ΔCatchment('000)	112	146	3,651	-9,220	-638	-54	-0.61	20,259
Small airports	28	-376	1,330	-6,991	-99	-27	-2	11
Big airports	28	2,137	6,536	-9,220	-1,334	1,161	5,975	20,259
Δ%Catchment	112	-12.61%	25.02%	-99.87%	-22.98%	-6.66%	-0.12%	43.11%
Small airports	28	-18.55%	25.57%	-99.87%	-24.54%	-10.65%	-2.11%	17.51%
Big airports	28	5.30%	16.70%	-28.77%	-7.48%	4.49%	15.81%	38.09%

Notes: Small airports: $\leq$ 25th percentile of annual flight volume; Large airports: $\geq$75th percentile.

Figure 4.7 displays the geographical distribution of airport catchment sizes and their HSR-induced changes. The visualization demonstrates that the most significant catchment expansion occurs at airports which already possess extensive road-based feeding networks. In contrast, airports with the smallest baseline catchments show minimal changes. This pattern suggests that even after accounting for HSR-induced inter-airport competition, the impacts remain unevenly distributed across catchment areas – manifesting as a siphoning effect. Specifically, HSR connectivity reinforces existing hub advantages by further concentrating passenger flows toward strategically located airports.

Notably, our analysis identifies at least one dominant regional hub in each geographic area that benefits from HSR integration:

- Northern: Beijing (PEK)
- Northeastern: Harbin (HRB) and Shenyang (SHE)
- Eastern Coastal: Shanghai (PVG & SHA), Hangzhou (HGH), and Nanjing (NKG)
- Central-Southern: Zhengzhou (CGO), Wuhan (WUH), and Changsha (CSX)
- Southwestern: Chengdu (CTU)
- Northwestern: Xi'an (XIY)
- Southeastern Coast: Guangzhou (CAN)

These regionally dominant airports, which already possessed strong pre-HSR market positions, demonstrate further catchment expansion post-HSR implementation. Despite that there are other regional hub airports experience decreased competitive advantages from HSR connections, such as Tianjin(TSN), Jinan (TNA), Qingdao (TAO), Chongqing (CKG), Xiamen (XMN), and Shenzhen (SZX), this phenomenon leads to increased traffic concentration at those established hubs, further suggesting that HSR connectivity amplifies rather than redistributes existing spatial inequalities in China's air transport network.

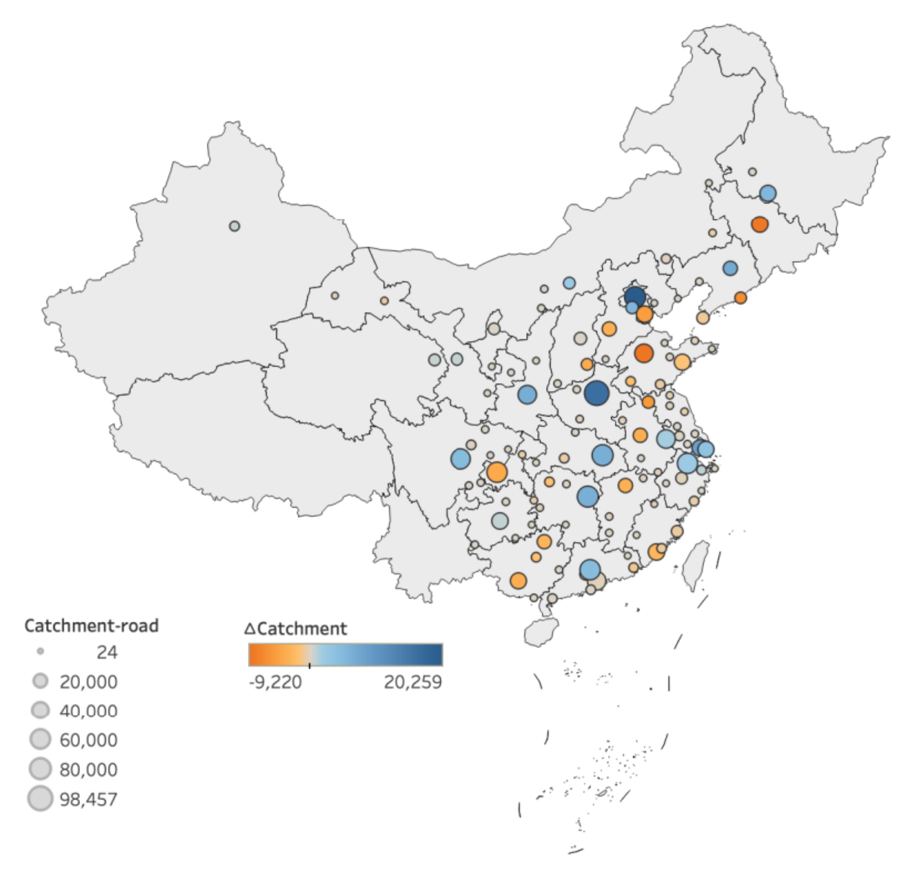


Figure 4.7: Spatial distribution of airport catchment size

4.5 Conclusions and discussions

This study investigates HSR's impact on airport catchment areas and competition. Two dimensions of catchment areas are considered: (1) spatial market reach (geographic coverage) and (2) accessible market base (considering airport's market share in catchment areas). Our analysis employs a comprehensive passenger-centric simulation that models complete door-to-door intercity feeding trip and defines airport catchment areas and competition at passenger OD market level. We develop multiple quantitative metrics to precisely characterize airport catchment area and competition. The HSR effect is isolated through counterfactual-style analysis, comparing a baseline road-only feeding network with a road+HSR connection scenario.

Our results reveal that the overall impact of HSR at OD level is more modest than often assumed. Over 80% of OD markets experience no change in competition intensity and the average travel times across markets show minimal system-wide reduction, indicating that HSR creates limited competitive pressures and limited improvements in connectivity at the market level. This is because most cities already achieve efficient airport access through existing road networks, and the extra market reach created by HSR is only relevant to a narrow subset of cities located beyond practical road-access distances. Although HSR is fast, the inherent friction of air-rail transfers (including schedule coordination penalties) makes HSR-feeding infeasible or not competitive in our context. This is particularly a problem at small airports due to low flight frequency and low frequency of HSR trains directly connecting to cities at a longer distance. As a result, although HSR in China does increase competition among airports, the magnitude is very mild.

HSR is found to expand an airport's market reach, with the most substantial effects observed at airports already possessing extensive road-based feeding networks, and airports with high flight densities. Regarding catchment size that incorporates both population and airport market share, this spatial unevenness remains. Notably, the geographic visualization reveals that many dominant airports in each geographic region consistently strengthen their positions through HSR connections, further expanding their catchment areas. Conversely, airports with minimal baseline catchment sizes show negligible changes, suggesting HSR primarily reinforces existing hierarchical patterns in China's air transport network rather than redistributing market access.

Our findings suggest that without deliberate policy intervention, HSR expansion may actually widen existing accessibility gaps between well-connected hubs and underserved regional airports. The potential air-HSR integration may exacerbate regional disparities. Furthermore, HSR may not fully alleviate congestion problems at major hub airports, as passengers may be attracted to larger airports due to higher flight frequencies and more convenient HSR-air transfers. Therefore, to foster regional balance and reduce congestion, policymakers should prioritize policies encouraging air-HSR integration (such as schedule coordination) at smaller airports and improve HSR station-airport connections to decrease the total travel time and thus balance the competitiveness of all airports.

Chapter 5

Conclusions

This thesis has systematically examined the multifaceted impacts of HSR on air transport through three interconnected studies, revealing complex interactions that reshape airline pricing and passenger volumes, scheduling strategies, and airport catchment dynamics. Collectively, these findings demonstrate that HSR's influence extends far beyond simple traffic diversion, creating nuanced competitive pressures and strategic dilemmas for airlines while reconfiguring the spatial and competitive landscape of airport systems.

The first study highlights the critical role of airfare adjustments in channeling HSR's impact on air traffic. While HSR entry typically reduces demand on routes where it holds strong time advantages (TTD $<$ 5 hours), airlines' fare reductions on medium-quality routes (TTD 5-9 hours) can offset diversion effects and even stimulate net traffic growth. These pricing responses vary significantly by market structure – airlines cut fares in less competitive markets but raise them in highly contested ones, amplifying traffic losses where competition is already intense. Notably, HSR's feeding effect emerges as a dominant force, generating 16.5 million additional passengers (6% of sample traffic), though with substantial environmental costs (2.17 million tons of CO_2). Without fare adjustments, these figures would nearly double, underscoring how airline pricing strategies fundamentally alter HSR's net effects.

The second study shifts focus to airline scheduling, revealing constrained strategic responses to HSR competition in specific market segments. On short-haul routes where HSR's advantages are strongest, airlines face difficult trade-offs: they cluster flights at peak times to retain demand, but this comes at the cost of reduced schedule differentiation. In contrast, on long-haul routes and in slot-controlled airports – where HSR poses milder competition – they maintain greater flexibility to differentiate schedules. This divergence in responses highlights how airlines' strategic options become constrained in markets most affected by HSR, potentially leading to intensified competition among airlines themselves. These findings complement conventional wisdom about competitive responses by showing that intermodal rivals like HSR elicit fundamentally different behaviors than traditional airline competitors.

The third study presents an analysis of how HSR reconfigures airport catchment dynamics through a novel itinerary-centric methodology. By simulating door-to-door travel times across China's integrated transport network, we evaluate airport's catchment areas at itinerary levels. The results reveal that HSR's benefits are unevenly distributed: while it expands the catchment areas of major hubs with dense flight networks, smaller airports see negligible gains, and system-wide competition intensifies only modestly. Crucially, HSR's potential to redistribute demand is hampered by the inherent inefficiencies of air-rail transfers, which limit its competitiveness against existing road-based feeding networks. The result is a self-reinforcing hierarchy where dominant airports grow stronger, while smaller regional airports struggle to benefit. This spatial imbalance suggests that unguided air-HSR integration plans may inadvertently deepen disparities in China's air transport network.

Together, these studies yield critical insights for policymakers and industry stakeholders. First, HSR's environmental and competitive impacts cannot be assessed without accounting for airline pricing strategies and induced demand due to HSR's feeding effect. Second, the uneven distribution of HSR's catchment benefits underscores the need for targeted policies –such as improved HSR-airport linkages and schedule coordination at small airports – to prevent further concentration of air traffic at major hubs.

Future research could explore the determinants of passengers' choices regarding intercity feeder trips, including their selection of connecting airports, once disaggregate data becomes available. A deeper understanding of the trade-offs between connection time and ticket price would enable airlines and airports to develop more effective customer acquisition strategies. Additionally, such analysis would allow for a more precise identification of competing airports, better reflecting real-world market dynamics. As HSR networks continue to expand globally, this thesis provides a foundational framework for understanding their transformative – and often paradoxical – effects on air transport systems. The overarching lesson is clear: effective integration of HSR and aviation systems requires tailored, market-specific approaches that carefully balance operational efficiency, regional equity, and environmental sustainability in developing multimodal transport networks.

Appendix A

Appendices for Chapter 2

A.1 List of sample airports

Table A.1: List of sample airports

Airport code	City
CAN	Guangzhou
CGO	Zhengzhou
CKG	Chongqing
CSX	Changsha
CTU	Chengdu
DLC	Dalian
HAK	Haikou
HGH	Hangzhou
KMG	Kunming
NKG	Nanjing
PEK	Beijing
PVG/SHA[a]	Shanghai
SHE	Shenyang
SYX	Sanya
SZX	Shenzhen
TAO	Qingdao
URC	Urumqi
WUH	Wuhan
XIY	Xi'an
XMN	Xiamen

Notes: [a] Airports located in the same city are aggregated. Specifically, Shanghai Pudong Airport (PVG) and Shanghai Hongqiao Airport (SHA) are considered as one origin/destination.

A.2 List of sample airlines and their ownership

Table A.2: List of sample airlines and their ownership

IATA code	Airline name	Ownership
3U	Sichuan Airlines	
8L	Lucky Air	
9C	Spring Airlines	
AQ	9 Air	HO
BK	Okay Airways	
CA	Air China	
CN	Grand China	HU
CZ	China Southern Airlines	
DR	Ruili Airlines	
DZ	Donghai Airlines	
EU	Chengdu Airlines	
FM	Shanghai Airlines	MU
FMF	Xiamen Airlines	
G5	China Express Airlines	
GJ	Loong Air	
GS	Tianjin Airlines	HU
HO	Juneyao Airlines	
HU	Hainan Airlines	
JD	Beijing Capital Airlines	HU
JR	Joy Air	MU
KN	China United Airlines	MU
KY	Kunming Airlines	CA
MU	China Eastern Airlines	
NS	Hebei Airlines	MF
PN	West Air	HU
QW	Qingdao Airlines	
SC	Shandong Airlines	CA
TV	Tibet Airlines	
UQ	Urumqi Air	HU
ZH	Shenzhen Airlines	CA

A.3 Sensitivity checks regarding the cut-off for pre-entry competition level

Considering the route composition and to keep an effective size of each subsample, we conduct robustness check by assigning routes with pre-entry HHI less than 0.35 to the high competition subsample and those with pre-entry HHI larger than 0.4 to the low competition subsample. The estimation results are shown in Table A.3 and Table A.4. Compared with Table 2.9 and Table 2.10, most coefficients are consistent in signs. A few coefficients possess different levels of statistical significance. Only the coefficients of D3 (representing routes with TTD between 5 and 7 hours) change in both sign and statistical significance level in the aircraft size equation in both subsamples. However, in general, these differences do not change our findings qualitatively.

Table A.3: Regression results of routes with pre-entry HHI<0.35 (high competition)

DepVar:	Pax		Fare	Aircraft size
Models:	Eq.(2.1)	Eq.(2.2)	Eq.(2.3)	
	(1)	(2)	(3)	(4)
Fare	-403.3***			
	(51.16)			
TTD<3h (D1)	-6,514***	-12,477***	14.11***	-5.466***
	(1,682)	(997.0)	(3.017)	(1.347)
3h<TTD<5h (D2)	-5,826***	-8,599***	6.774***	-4.209***
	(1,350)	(865.4)	(2.610)	(1.170)
5h<TTD<7h (D3)	-511.5	-432.0	0.0349	1.900**
	(891.4)	(591.6)	(1.776)	(0.800)
7h<TTD<9h (D4)	-1,014	-1,806***	1.840	-3.558***
	(747.5)	(491.6)	(1.485)	(0.664)
TTD>9h (D5)	2,466***	1,634***	3.768**	-2.641***
	(821.7)	(540.9)	(1.629)	(0.731)
Feeding	74.90***	70.62***	0.0650**	0.126***
	(15.50)	(10.29)	(0.0273)	(0.0139)
HSRmonth	102.9***	12.36	0.273***	-0.0574*
	(36.90)	(23.27)	(0.0689)	(0.0315)
LCCshare	85.91	6,307***	-1.601	-4.880*
	(3,239)	(2,085)	(6.311)	(2.818)
RouteGDP	0.0694*	-0.00837		-0.000144***
	(0.0393)	(0.0253)		(3.41e-05)
RoutePop	4.170***	0.266		0.000981
	(0.842)	(0.452)		(0.000610)
HHI			44.28***	
			(4.592)	
Constant	-22,300	20,343**	109.3***	145.5***
	(15,857)	(9,894)	(1.905)	(13.37)
Three-way FE	✓	✓	✓	✓
Observations	3,888	3,888	3,888	3,888
R-squared		0.295	0.295	0.229
Number of routes	81	81	81	81

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.4: Regression results of routes with pre-entry HHI>0.4 (low competition)

DepVar:	Pax		Fare	Aircraft size
Models:	Eq.(2.1)	Eq.(2.2)	Eq.(2.3)	
	(1)	(2)	(3)	(4)
Fare	-325.8***			
	(43.99)			
TTD<3h (D1)	-18,593***	-20,727***	7.742	-9.081*
	(4,244)	(3,161)	(9.220)	(4.757)
3h<TTD<5h (D2)	-6,473***	-3,706**	-7.474*	0.684
	(1,974)	(1,447)	(4.169)	(2.178)
5h<TTD<7h (D3)	330.4	3,258***	-5.582*	-8.590***
	(1,428)	(1,024)	(2.965)	(1.541)
7h<TTD<9h (D4)	-1,261	2,752***	-9.348***	-0.123
	(1,485)	(1,033)	(3.026)	(1.554)
TTD>9h (D5)	1,665	110.5	7.669***	7.227***
	(1,284)	(946.0)	(2.761)	(1.423)
Feeding	78.98***	50.38***	0.160***	0.0128
	(21.42)	(15.73)	(0.0422)	(0.0237)
HSRmonth	262.8***	48.60	0.717***	0.0237
	(55.88)	(35.70)	(0.0914)	(0.0537)
LCCshare	1,828	18,454***	-29.00***	7.829
	(5,048)	(3,376)	(10.14)	(5.080)
RouteGDP	0.0676	-0.0359		-0.000249***
	(0.0625)	(0.0455)		(6.85e-05)
RoutePop	1.200*	-0.280		-0.00195**
	(0.703)	(0.504)		(0.000758)
HHI			38.82***	
			(3.768)	
Constant	33,612**	33,013***	116.1***	228.1***
	(16,340)	(12,200)	(2.574)	(18.36)
Three-way FE	YES	YES	YES	YES
Observations	1,824	1,824	1,824	1,824
R-squared		0.309	0.378	0.154
Number of routes	38	38	38	38

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.4 Computation of individual determinants' total impacts

Table A.5 lists the formula for calculating the total (direct plus indirect) impacts of each variable if that variable changes by one unit. These expressions are obtained from solving the system of equations and evaluated with the estimated coefficients after the 3SLS procedure. The corresponding estimated values are presented in the third and fourth columns of Table 11.

Table A.5: Regression results of routes with pre-entry HHI>0.4 (low competition)

Variable	Total impact on air traffic	Total impact on airfare
Dm	$\frac{\alpha_m + \alpha_6\delta_m}{1-\alpha_6\delta_6}$	$\frac{\delta_m + \alpha_m\delta_6}{1-\alpha_6\delta_6}$
Feeding	$\frac{\alpha_7 + \alpha_6\delta_7}{1-\alpha_6\delta_6}$	$\frac{\delta_7 + \alpha_7\delta_6}{1-\alpha_6\delta_6}$
HSRmonth	$\frac{\alpha_8 + \alpha_6\delta_8}{1-\alpha_6\delta_6}$	$\frac{\delta_8 + \alpha_8\delta_6}{1-\alpha_6\delta_6}$
LCCshare	$\frac{\alpha_9 + \alpha_6\delta_9}{1-\alpha_6\delta_6}$	$\frac{\delta_9 + \alpha_9\delta_6}{1-\alpha_6\delta_6}$
HHI	$\frac{\alpha_6\delta_{10}}{1-\alpha_6\delta_6}$	$\frac{\delta_{10}}{1-\alpha_6\delta_6}$
RouteGDP	$\frac{\alpha_{10}}{1-\alpha_6\delta_6}$	$\frac{\alpha_{10}\delta_6}{1-\alpha_6\delta_6}$
RoutePop	$\frac{\alpha_{11}}{1-\alpha_6\delta_6}$	$\frac{\alpha_{11}\delta_6}{1-\alpha_6\delta_6}$

A.5 Average CO2 emissions per passenger

Table A.6: Average CO2 emissions per passenger(Kg)

City pair	CO2/pax	City pair	CO2/pax	City pair	CO2/pax	City pair	CO2/pax
CANCGO	115.9	CKGPVG	132.6	DLCKMG	N.A.	NKGSZX	108.7
CANCKG	97.2	CKGSHE	167.5	DLCNKG	90.7	NKGTAO	64.8
CANCSX	65.4	CKGSYX	121.4	DLCPEK	57.4	NKGXIY	101.6
CANCTU	113.5	CKGSZX	100.9	DLCPVG	92.5	NKGXMN	87.5
CANDLC	162.8	CKGTAO	132.0	DLCSZX	162.6	PEKPVG	99.5
CANHAK	60.6	CKGURC	184.7	DLCTAO	46.1	PEKSHE	70.4
CANHGH	99.9	CKGWUH	86.0	DLCWUH	107.6	PEKSZX	147.6
CANKMG	94.4	CKGXIY	71.1	DLCXIY	122.5	PEKTAO	63.5
CANNKG	104.3	CKGXMN	117.1	DLCXMN	137.2	PEKURC	186.8
CANPEK	143.5	CSXCTU	96.0	HAKHGH	134.3	PEKWUH	104.3
CANPVG	109.8	CSXDLC	129.9	HAKKMG	96.1	PEKXIY	94.1
CANSHE	179.6	CSXHAK	99.0	HAKNKG	136.4	PEKXMN	144.8
CANSYX	79.4	CSXHGH	82.1	HAKPEK	178.6	PVGSHE	111.7
CANTAO	138.2	CSXKMG	101.3	HAKPVG	143.6	PVGSZX	115.1
CANWUH	86.0	CSXNKG	77.9	HAKSZX	58.5	PVGTAO	72.7
CANXIY	118.9	CSXPEK	117.1	HAKWUH	117.7	PVGWUH	79.2
CANXMN	66.1	CSXPVG	94.3	HAKXIY	141.4	PVGXIY	118.2
CGOCKG	91.4	CSXSHE	151.6	HAKXMN	96.3	PVGXMN	86.0
CGOCTU	99.6	CSXSYX	109.9	HGHKMG	157.2	SHESZX	190.0
CGODLC	90.5	CSXSZX	73.8	HGHPEK	108.2	SHETAO	76.0
CGOHAK	145.4	CSXTAO	107.3	HGHSHE	122.0	SHEWUH	133.3
CGOHGH	88.3	CSXXIY	88.0	HGHSYX	146.3	SHEXIY	136.8
CGOKMG	127.9	CSXXMN	72.7	HGHSZX	104.2	SHEXMN	165.2
CGONKG	71.5	CTUDLC	156.2	HGHTAO	81.1	SYXSZX	75.5
CGOPEK	75.1	CTUHAK	122.4	HGHWUH	75.2	SYXWUH	125.2
CGOPVG	82.8	CTUHGH	137.9	HGHXIY	111.4	SYXXIY	152.5
CGOSHE	113.5	CTUKMG	70.3	HGHXMN	75.1	SYXXMN	108.5
CGOSYX	155.6	CTUNKG	124.5	KMGNKG	156	SZXTAO	143.5
CGOSZX	119.7	CTUPEK	127.1	KMGPEK	170.6	SZXWUH	88.4
CGOTAO	76.6	CTUPVG	142.5	KMGPVG	158.2	SZXXIY	127.3
CGOURC	197.9	CTUSHE	175.1	KMGSYX	94.3	SZXXMN	N.A.
CGOXMN	110.4	CTUSYX	129.2	KMGSZX	105.9	TAOWUH	86.5
CKGCSX	77.5	CTUSZX	120.0	KMGTAO	162.1	TAOXIY	106.0
CKGDLC	153.2	CTUTAO	139.8	KMGWUH	118.0	TAOXMN	120.4
CKGHAK	111.4	CTUURC	174.1	KMGXIY	111.9	URCXIY	172.3
CKGHGH	122.6	CTUWUH	92.1	KMGXMN	129.4	WUHXIY	75.9
CKGKMG	73.1	CTUXIY	79.5	NKGPEK	95.9	WUHXMN	84.4
CKGNKG	115.5	CTUXMN	130.4	NKGSHE	113.3	XIYXMN	128.3
CKGPEK	128.4	DLCHGH	98.4	NKGSYX	151.1		

Notes: The table presents average CO2 emissions per passenger in economy class for a one-way trip between two cities. There are no records for routes DLCKMG and SZXXMN, and we leave them blank in the table.

A.6 Average monthly traffic changes due to price-irrelevant effects

Table A.7: Average monthly traffic changes due to price-irrelevant effects by route type and year

	TTD					Non-HSR	Total
year	<3h	3-5h	5-7h	7-9h	>9h[a]		
2012	-7108	4161	8669	12067		1976	2290
2013	-2182	3715	9539	5451		2897	3394
2014	-1812	5046	9619	5021	8441	2770	4041
2015	2333	9854	12197	9372	12013	4286	7045
Total	-1724	6182	10348	7951	10752	2843	4193

Notes: [a] In 2012 and 2013, no observations fall into this category.

A.7 Pricing regulations on air passenger flights in China

Table A.8: Pricing regulations on air passenger flights in China

Year	Route / fare class	Regulated price range	Base fare (P)
2004	All routes	0.55P ~1.25P	2004 level
2010	All routes, first and business classes	No limit	
	All routes, economy class	0.55 ~1.25P	2004 level
2013	(a) Routes competing with ground transport and served by two or more airlines	No limit	
	Routes not belonging to (a)	<1.25P	2004 level
2014	(b) Routes competing with ground transport and connecting cities from two adjacent provinces	No limit	
	Routes not belonging to (a) or (b)	<1.25P	2014 level
2016	(c) Routes with distance <800 km; or distance >800 km and served by HSR	No limit	
	Routes not belonging to (a), (b) or (c)	<1.25P	2014 level
2017	(d) Routes served by five or more airlines	No limit	
	Routes not belonging to (a), (b), (c) or (d)	<1.25P	2014 level
2020	(e) Routes served by three or more airlines	No limit	
	Routes not belonging to (a), (b), (c) or (e)	<1.25P	2014 level

Notes: "P" under regulated price range represents the base fare. Since 2004, $P = 0.75 \times distance$. From 2014 onward, $P = log_{distance \times 0.6} 150 \times distance \times 1.3$ for the plateau routes and $P = log_{distance \times 0.6} 150 \times distance \times 1.1$ for other routes. The first and business classes have been fully liberalized since 2010, and hence they are not mentioned in the table after 2013.

Appendix B

Appendices for Chapter 3

B.1 Representative days of each flight season

Table B.1: Representative days of each flight season

Flight season	Representative days	Flight season	Representative days
	17/11/2008		12/11/2012
	15/12/2008		17/12/2012
2008 Winter	12/01/2009	2012 Winter	17/01/2013
	16/02/2009		18/02/2013
	16/03/2009		18/03/2013
	16/11/2009		18/11/2013
	14/12/2009		16/12/2013
2009 Winter	18/01/2010	2013 Winter	13/01/2014
	15/02/2010		17/02/2014
	15/03/2010		17/03/2014
	15/11/2010		17/11/2014
	13/12/2010		15/12/2014
2010 Winter	17/01/2011	2014 Winter	12/01/2015
	14/02/2011		16/02/2015
	14/03/2011		16/03/2015
	14/11/2011		16/11/2015
	12/12/2011		14/12/2015
2011 Winter	16/01/2012	2015 Winter	18/01/2016
	13/02/2012		18/02/2016
	12/03/2012		14/03/2016

B.2 Price effect of differentiation

The impact of differentiation on air ticket prices is identified by the following specification. The log of ticket price is regressed on the four differentiation indices separately and two control variables, the share of LCC and HHI. Similar to the main model, airline-route and time fixed effects are considered and standard errors are clustered at the market level.

$$Lnfare_{lmt} = \beta \mathbf{D}_{lmt} + \zeta \mathbf{X}_{lmt} + \lambda_{lm} + \mu_t + \varepsilon_{lmt} \tag{B.1}$$

Airline ticket price data is obtained from the IATA Airport Intelligence Services database. As we have only access to the routes linking the 20 biggest airports in China, the sample used here is different from that used in the main model. Table B.1 presents the results. It shows that the overall and between-firm differentiation have a statistically significant impact on airfare, although the magnitude of the impact is small: a ten-minute increase in closest between-airline differentiation results in a 2% increase in air price.

Table B.2: Impact of differentiation on flight price

DepVar:	Lnfare			
	(1)	(2)	(3)	(4)
D	0.000166***			
	(4.94e-05)			
WD		3.73e-06		
		(3.32e-05)		
BD			0.000180***	
			(4.99e-05)	
BD^{cls}				0.000231***
				(3.62e-05)
LCCshare	1.124*	2.029*	1.127*	1.080
	(0.668)	(1.068)	(0.671)	(0.688)
HHI	0.361***	0.331***	0.418***	0.361***
	(0.0709)	(0.0836)	(0.0734)	(0.0725)
Airline-route FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	10,781	6,565	10,702	10,702
R-squared	0.843	0.847	0.842	0.843

Notes: Standard errors are clustered at the market level and in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix C

Appendix for Chapter 4

C.1 HSR development in China

The table below shows the number of city pairs served by high-speed rail (HSR) in each year. Note that the numbers reported are directional, as some city pairs may not have service in both directions in certain years.

Table C.1: HSR coverage by year

Year	Number of city pairs
2008	646
2009	1,158
2010	1,481
2011	1,828
2012	1,954
2013	3,120
2014	3,962
2015	8,275

Source: Summarized by the authors based on National Rail Timetable of China.

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