https://doi.org/10.1016/j.tra.2022.09.016

Airline reactions to high-speed rail entry: rail quality and market structure

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January 2022; Revised: June 2022, September 2022

Abstract

Airfare reduction is proposed by a theoretical paper to be a possible source of observed air traffic increase in some markets where high-speed rail (HSR) enters and competes with airlines. This paper aims to empirically test whether and to what extent the air traffic impact is channeled by the adjustment in airfares. To understand the varying empirical results found in the literature, we examine heterogeneous airline responses in traffic and airfare in relation to HSR qualities measured by HSR-air travel time difference and pre-entry market structure of airline as well as decompose HSR impacts into competition, feeding and long-term effects. Using a panel dataset of Chinese air routes, we find that airfare adjustment plays crucial roles in channeling HSR's air traffic impact. Our estimation suggests that HSR introduced over 16.5 million additional passengers to the sampled air routes in our study period, generating 2.17 million tons of extra CO2 emissions from air flights. However, these numbers would increase to 32.2 million additional passengers and 3.4 million tons of extra CO2 emissions after removing the price adjustment.

Keywords: air-rail competition; airfare; high-speed rail quality; market structure; intermodal transport; China

Acknowledgement: We would like to thank participants of the 24th Air Transport Research Society (ATRS) World Conference and the 2021 Annual Conference of the International Transportation Economics Association (ITEA) as well as discussants of the 2021 German Aviation Research Society (GARS) junior workshop for helpful comments and discussion. Financial support from the Research Grants Council of Hong Kong (RGC/PolyU 152195/17E) is gratefully acknowledged.

1. Introduction

Till June 1st, 2021, the high-speed rail (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., 2019a), 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 paper 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 paper is organized as follows. Section 2 reviews the literature. Section 3 provides description of the sample and data. Section 4 describes the empirical models and variables. Section 5 presents the regression results and section 6 provides policy discussion and estimates changes in airline CO2 emissions due to the entry of HSR to our sample routes. Section 7 concludes the paper.

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; Li et al., 2019b) and on airfare (e.g., Cappoza, 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 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 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.

Table 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. (2019a)	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. (2019b)	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.

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.

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

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. (2020) 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.

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., González-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. Cappoza (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.

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 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. 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. 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.

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

Table 2 HSR service duration and number of routes

	Months of HSR operation (The first month of operation included)	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

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

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 paper. As highlighted by Gu and Wan (2020), due to the variations of railway 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 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 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.

[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.

In general, most routes have TTD between 3 and 7 hours.

Table 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 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.

Table 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

Note: 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.

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

[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., 2018).

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

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 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 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.

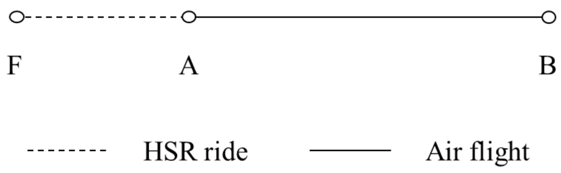

Figure 1. Illustration of the feeding city

Table 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

[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.

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 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

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:

$$Pax_{it} = \alpha_0 + \sum_{m=1}^{5} \alpha_m Dm_{it} + \alpha_6 Fare_{it} + \alpha_7 Feeding_{it} + \alpha_8 HSRmonth_{it} + \alpha_9 LCCshare_{it} + \alpha_{10} RouteGDP_{it} + \alpha_{11} RoutePop_{it} + route_i + year_t + month_t + \varepsilon_{it} \quad (1)$$

$$Pax_{it} = \beta_0 + \sum_{m=1}^{5} \beta_m Dm_{it} + \beta_6 Feeding_{it} + \beta_7 HSRmonth_{it} + \beta_8 LCCshare_{it} + \beta_9 RouteGDP_{it} + \beta_{10} RoutePop_{it} + route_i + year_t + month_t + \epsilon_{it} \quad (2)$$

$$Fare_{it} = \gamma_0 + \sum_{m=1}^{5} \gamma_m Dm_{it} + \gamma_6 Feeding_{it} + \gamma_7 HSRmonth_{it} + \gamma_8 LCCshare_{it} + \gamma_9 HHI_{it} + route_i + year_t + month_t + \mu_{it} \quad (3)$$

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, …, 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 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 / advantage 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 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. (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 3. As airfare is controlled in Eq. (1), dummy variables $D1_{it}$ ~ $D5_{it}$ 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) 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. (1). As airfare is not controlled in Eq. (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. (1) and Eq. (2) as empirical evidence of the significant role of price response in determining the ultimate impact on air 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. (3) specifies the impact of HSR entry on airfare. We assume all the HSR-related

[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.

features can have an impact on airfare, including HSR quality, feeding effect, and time lag effect. After estimating both Eq. (2) and Eq. (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. (1), (2) and (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 6. Summary statistics of main variables are listed in Table 7.

Table 6 Notations and definitions of variables in Eq. (1), (2) and (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

Table 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

Note: 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.

5. Results

5.1 Airline reactions to parallel HSR entry: heterogeneous HSR quality

Table 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. (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 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. (1) of Table 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.

Table 8 Regression results with full sample

Variables	DV = Pax		DV = Fare
	Eq. (1)	Eq. (2)	Eq. (3)
Fare	-379.3***		
	(33.10)		
HSR-air TTD groups			
Below 3 hours (D1)	-13,848***	-15,607***	4.827*
	(1,340)	(971.1)	(2.595)
3-5 hours (D2)	-6,876***	-3,459***	-8.802***
	(848.6)	(579.7)	(1.541)
5-7 hours (D3)	-390.8	1,731***	-5.132***
	(626.9)	(437.1)	(1.166)
7-9 hours (D4)	-474.9	1,080***	-4.289***
	(590.1)	(419.1)	(1.120)
Above 9 hours (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	YES	YES	YES
Observations	7,440	7,440	7,440
R-squared		0.259	0.326

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The third column of Table 8 presents estimation of airfare model Eq. (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 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) which does not control for airfare. Comparing the coefficients of TTD dummies in Eq. (2) with those in Eq. (1), we find the coefficients of D2, D3 and D4 in Eq. (2) are substantially increased while those of D1 and D5 see a slight decrease. Since HSR's impact on airfare is proved by Eq. (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. (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) than that in Eq. (1). Similarly, the mild increase in airfare on the routes with TTD above 9 hours slightly suppresses the air traffic increase in these routes.

5.2 Airline reactions to HSR feeding opportunities

We observe a strong positive impact of HSR feeding cities on air traffic in Table 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. (1) and Eq. (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. (3) probably because HSR's ability to feed air routes enhances the demand for air transport.

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 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~D5 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 8.

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. (1) – (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. (3) in Table 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

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

[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).

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). The OLS estimation results are listed in the fourth column of Table 9. Clearly, aircraft size decreases in all cases of TTD, which is consistent to our conjecture. By comparing the coefficients of D1~D5 in the first and second columns of Table 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 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 9).

Table 9 Regression results of routes with high level of competition pre-entry (HHI < 0.3)

	DV = Pax		DV = Fare	DV = Aircraft
VARIABLES	Eq. (1)	Eq. (2)	Eq. (3)	size
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	YES	YES	YES	YES
Observations	2,592	2,592	2,592	2,592
R-squared		0.275	0.363	0.268
Number of routes	54	54	54	54

[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.

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

However, when the pre-entry competition level is low (Table 10), airfare only significantly increases on routes with TTD below 3 hours with a statistically significant 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 10), similar to what we have found with the full sample in Section 5.1. On the other hand, if airfare were unchanged (the first columns of Tables 9 and 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 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.

Table 10 Regression results of routes with low level of competition pre-entry (HHI > 0.3)

	DV = Pax		DV = Fare	DV = Aircraft
VARIABLES	Eq. (1)	Eq. (2)	Eq. (3)	size
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	YES	YES	YES	YES
Observations	3,984	3,984	3,984	3,984
R-squared		0.311	0.338	0.144
Number of routes	83	83	83	83

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

Similar to the findings in Section 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.

5.5 Sensitivity check with 3SLS

As mentioned in Section 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 between airfare and air traffic by estimating Eq. (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. (1) and Eq. (2), as well as the mediation effect of airfare on air traffic. In this case, the impact of HSR on airfare modeled in Eq. (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. 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).

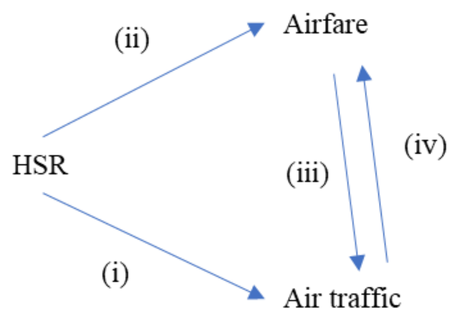

Figure 2. Illustration of HSR impact

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. (3) into Eq. (4) by adding Pax_{it} as a predictor of airfare. As air traffic is controlled in Eq. (4), HSR variables in this equation now capture the direct effect on airfare that is irrelevant to passenger number change.

$$
\begin{aligned}
Fare_{it} = \delta_0 + \sum_{m=1}^{5} \delta_m Dm_{it} + \delta_6 Pax_{it} + \delta_7 Feeding_{it} + \delta_8 HSRmonth_{it} \\
+ \delta_9 LCCshare_{it} + \delta_{10} HHI_{it} + route_i + year_t + month_t + \mu_{it}
\end{aligned}
\tag{4}
$$

We treat Eq. (1) and Eq. (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, 1992). 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 D.

Regression results using 3SLS and individual variables' total impacts are listed in Table 11. Comparing the first column in Table 11 and the first column in Table 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 8 and the third column in Table 11 for the total impacts of HSR on air traffic and comparing the third column in Table 8 and the fourth column in Table 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.

Table 11 Regression results with 3SLS approach (full sample)

Variables	DV=Pax Eq. (1)	DV=Fare Eq. (4)	Total impact on air traffic	Total impact on airfare
Fare	-378.4***			
	(32.67)			
Pax		-0.00991*		
		(0.00601)		
HSR-air TTD groups				
Below 3 hours (D1)	-13,667***	-143.4	-14,765.61***	2.904
	(1,320)	(90.43)	(953.8)	(2.566)
3-5 hours (D2)	-6,695***	-39.92**	-3,057.9***	-9.611***
	(834.5)	(19.71)	(565.7)	(1.554)
5-7 hours (D3)	-332.3	10.78	1,603.4***	-5.115***
	(618.3)	(10.56)	(423.6)	(1.151)
7-9 hours (D4)	-485.9	5.766	969.97**	-3.847***
	(582.4)	(7.361)	(407.6)	(1.098)
Above 9 hours (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	YES	YES		
Observations	7,440	7,440		

Note: The first and second columns represent HSR's direct impacts. The first column is comparable to the first column in Table 8. The third and fourth column represent HSR's total impact and are comparable to the second and third columns in Table 8. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Policy implications

HSR has been advocated by policy makers because it emits less greenhouse gas (GHG) such as CO_2 and NOx than air transport on a per-seat basis (e.g., EC, 2011; TRB, 2013). Substituting air flights by HSR on short-haul routes may benefit the environment. However, in Section 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 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.

6.1 Air traffic and emission effects with airfare adjustment

Regression results obtained from Eq. (2) in Table 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. (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.

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

CO2 emission change is computed as

$$\Delta E_{it} = r_i \cdot \Delta Pax_{it} \tag{6}$$

where r_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

[11] Refer to ICAO Carbon Emissions Calculator Methodology for details (https://www.icao.int/environmental-protection/CarbonOffset/Documents/Methodology%20ICAO%20Carbon%20Calculator_v11-2018.pdf).

listed in Appendix E.

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

Table 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 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	< 3 h	3-5 h	5-7 h	7-9 h	> 9 h [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

Note: 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

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 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

Note: 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 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.

6.2 Price-irrelevant air traffic and emission effects

As shown in Section 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. (5) and Eq. (6), except that the calculation is based on the estimation of Eq. (1) in Table 8 instead of Eq. (2).

The total effect and price-irrelevant effect are compared in Table 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 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 F.

Table 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

Note: 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. (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 12.

Table 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.

Table 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

Note: “Price-irrelevant” columns show the effects based on Eq. (1), while the “Total” columns present the effects based on Eq. (2), which add up price-irrelevant effect and price-relevant effect.

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 CO2 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 CO2 emission increase during the sampling period (estimated in Section 6.1) might be considered as a lower bound of system-wide CO2 emission change which adds up CO2 emissions from airlines and HSR.

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 CO2 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.

6.3 Airfare regulation

Civil aviation administration of China (CAAC) has been progressively lifting airfare regulation in recent years as summarized in Appendix G. 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 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.

7. Concluding remarks

This paper 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., 2019b), 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 CO_2 emissions requires an assessment on not only changes in airlines' CO2 emission but also CO_2 emissions of HSR operation to serve passengers diverted from airlines and induced trips of intermodal service. Third, 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.

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Appendix A

Table A 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

Note: 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.

Appendix B

Table B 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

Appendix C 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 C.1 and Table C.2. Compared with Table 9 and Table 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 C.1 Regression results of routes with pre-entry HHI < 0.35 (high competition)

	DV = Traffic		DV = Fare	DV = Aircraft
VARIABLES	Eq. (1)	Eq. (2)	Eq. (3)	size
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	YES	YES	YES	YES
Observations	3,888	3,888	3,888	3,888
R-squared		0.295	0.295	0.229
Number of routes	81	81	81	81

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.2 Regression results of routes pre-entry HHI > 0.4 (low competition)

	DV = Traffic		DV = Fare	DV = Aircraft size
VARIABLES	Eq. (1)	Eq. (2)	Eq. (3)	
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

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix D

Table D 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 D Computation of individual determinants' total impacts

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	$\frac{\alpha_{11}}{1-\alpha_6\delta_6}$	$\frac{\alpha_{11}\delta_6}{1-\alpha_6\delta_6}$

Appendix E

Table E Average CO_2 emissions per passenger (Kg)

City pair	CO_2/pax	City pair	CO_2/pax	City pair	CO_2/pax	City pair	CO_2/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	DLCSZX	162.6	PEKPVG	99.5
CANHAK	60.6	CKGURC	184.7	DLCTAO	46.1	PEKSHE	70.4
CANHGH	99.9	CKGWUH	86	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	HAKHGH	134.3	PEKWUH	104.3
CANPVG	109.8	CSXDLC	129.9	HAKKMG	96.1	PEKXIY	94.1
CANSHE	179.6	CSXHAK	99	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	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
CGOCTU	99.6	CSXSYX	109.9	HGHKMG	157.2	SHESZX	190
CGODLC	90.5	CSXSZX	73.8	HGHPEK	108.2	SHETAO	76
CGOHAK	145.4	CSXTAO	107.3	HGHSHE	122	SHEWUH	133.3
CGOHGH	88.3	CSXXIY	88	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	KMGTAO	162.1	TAOXIY	106
CKGDLC	153.2	CTUTAO	139.8	KMGWUH	118	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		

Note: The table presents average CO_2 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.

Appendix F

Table F Average monthly traffic changes due to price-irrelevant effects by route type and year

	TTD						
year	< 3 h	3-5 h	5-7 h	7-9 h	> 9 h [a]	Non-HSR	Total
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

Note: a. In 2012 and 2013, no observations fall into this category.

Appendix G

Table G 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

Note: "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 $log_{distance \times 0.6}150 \times distance \times 1.1$ 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.