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Zhang, R, Johnson, D orcid.org/0000-0002-1188-8610, Zhao, W orcid.org/0000-0002-5481-8700 et al. (1 more author) (2019) Competition of airline and high-speed rail in terms of price and frequency: Empirical study from China. Transport Policy, 78. pp. 8-18. ISSN 0967-070X

https://doi.org/10.1016/j.tranpol.2019.03.008

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Competition of airline and high-speed rail in terms of price and frequency: empirical study from China

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Abstract

High-speed rail (HSR) is developing at an unprecedented speed in China, however its impact on the air market is under-investigated. In order to fully assess strategic response behaviour, two aspects of competition should be considered: fares and frequency. We present the first ex-post analysis of HSR's influence on both air pricing and frequencies in China using a panel dataset of 30 different routes. In modelling frequency we use a novel application of Instrumental Variables to address the potential bias arising from the co-dependency between modal frequencies. Our results indicate that the presence of inter-modal competition can induce air to reduce fares and frequencies greatly: air fares are 0.397 CNY/km (34%) lower and air frequencies are 60.2% less on the routes with HSR. Where competition from HSR exists, air fares and frequencies are found to be higher on the routes with lower HSR frequencies and lower air travel times relative to those of HSR. We find that the inter-temporal price discrimination (IPD) of air fares can also be influenced by HSR competition: the J-curve of air prices reaches a minimum value earlier, i.e. more days ahead of departure, on the routes with HSR services. Air fares' variation by distance is also influenced by HSR competition: fares per kilometre reach their minimum at longer distances (around 1500km) on the routes with HSR services.

Keywords: Airline; High-speed rail; Inter-modal competition; Pricing; Frequency

1. Introduction

The expansion of the high-speed rail (HSR) network in Europe and Asia has led to major changes in the inter-city high-speed transport market, which was previously dominated by airlines. Before the introduction of HSR, traditional rail could not compete with air at distances around 500km and over, given their relatively high journey time. Now owing to the similar characteristics of their services and generalized travel costs, HSR has become the main competitor for air transport in the medium-distance transport market (Capon et al., 2003; Fu et al., 2012; Milan, 1993).

In Japan where the first HSR was introduced, Shinkansen has a larger market share than air transport for distances under 700 km because of higher-frequency, easier access, cheaper and more reliable services (Taniguchi, 1992). In Europe, after the introduction of TGV Sud-Est between Paris and Lyon in 1981, the market share for air dropped from 31% to 7%. The same phenomenon was also witnessed in Spain: after the AVE service was introduced between Madrid and Seville in 1992, air market share dropped from 40% to 13% (COST 318, 1998; Nash, 2009).

China has the most aggressive HSR development strategy amongst all countries with HSR, commencing in 2008: by the end of 2015 a network of 19,000 km had been put into service. This unprecedented growth has led to significant traffic reallocation in the Chinese transport market. Flights for more than ten city pairs were cancelled after the opening of the corresponding HSR routes, e.g., Zhengzhou-Xi'an,

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Nanjing-Wuhan, Wuhan-Nanchang. Air traffic decreased by 60% and 40% respectively for the city pairs of Changsha-Guangzhou and Wuhan-Guangzhou after the introduction of Wuhan-Guangzhou HSR in December 2009 (Bullock et al., 2012; Fu et al., 2012; Yang and Zhang, 2012). Studies by the Civil Aviation Administration of China (CAAC), the official Chinese air transport regulator, have shown that air traffic is expected to decrease 50% on routes around 500 km and 20% on routes around 800 km when new HSR services are introduced (Albalate et al., 2015; Gaultier Ross, 2015).

Table 1 Related ex-post econometric studies of the impact of HSR operation on air transport

Paper	Market	Data	Method	Variables	Main Results
1. Demand side influence: Airline passenger volume and turnover					
Zhang et al. (2018)	1178 routes in East Asia	Route-level yearly panel data	D-in-D estimation, **no** HSR characteristics considered	DV: air passenger volume; IV: HSR_D, year, population, GDP, access distance, distance*HSR_D	The airport's access distance is negatively related to air traffic. The substitution effects of HSR are the most significant on routes below 1000km.
Li et al. (2019)	642 routes in China	Route-level yearly panel data	D-in-D estimation, HSR travel time, fare and frequency are considered	DV: air passenger volume; IV: GDP, population, internet usage, distance, average air fare, HSR travel time, HSR fare, HSR average frequency	HSR leads to 50% declines in air travel in China. HSR frequency is negatively related to air travel.
Zhang and Zhang (2016)	239 routes in China	Route-level yearly panel data	Gravity model, **no** HSR characteristics considered	DV: air passenger volume; IV: GDP, employees in financial industry, expenditure, year, distance, HSR_D, lcc_D, airline numbers, policy_D, hub_D	The presence of HSR services would reduce the bilateral air passenger flows by 53%.
Clewlow et al. (2014)	90 airport pairs in Europe	Route-level yearly panel data	OLS, RE-GLS, HSR in-vehicle time considered	DV: air passenger volume; IV: GDP, fuel price, population, density, hub_D, lcc_D	The improvement of rail travel times was found to be a significant factor in reducing short-haul air traffic in Europe.
Zhang et al. (2017)	92 routes in China	Route-level quarterly panel data	RE model, FE model, FGLS, HSR frequency, travel time are considered	DV: air passenger turnover; IV: air yield, population, GDP, distance, tourism city_D, lcc_D, price difference, HSR frequency, HSR travel time	Price difference and HSR frequency have negative effects while HSR travel time has a positive effect on air passenger traffic
2. Supply side influence: Airline frequencies and seats offered					
Albalate et al. (2015)	180 domestic routes in Europe	Route-level yearly panel data	RE-GLS, **no** HSR characteristics considered	DV: seat number, frequency; IV: population, GDP, distance, hub_D[‡], HSR_D, HHI, lcc_D, country_D, year_D	Intermodal competition from HSR can reduce air seats, but the reduction effect for flight numbers is not significant.
Jiménez and Betancor (2012)	9 routes in Spain	Route-level monthly panel data	2SLS-IV, **no** HSR characteristics considered	DV: frequency; IV: air passengers, train passengers, Iberia's market share, distance, HSR_D, summer_D, other route_D	The presence of HSR service can reduce airline frequencies by 17%.

[‡] _D denotes dummy variable.

Dobruszkes et al. (2014)	161 city pairs in Europe	Route-level cross-sectional data	Weighted CLAD, HSR in-vehicle time, boarding time and frequency are considered	DV: seat number, frequency; IV: population, GDP, distance, hub_D, lcc share, HSR travel time, weekly HSR frequency, air rail integration, HSR service coverage, country_D	Shorter HSR travel times lead to fewer air seats and frequencies. HSR travel time has much more impact on air services than HSR frequency.
Wan et al. (2016)	467 routes in China, Japan, Korea	Route-level yearly panel data	D-in-D estimator with PSM approach, **no** HSR characteristics considered	DV: seat number; IV: HSR_D, GDP, population, lcc_D, year, route	HSR entries lead to a more significant drop in airlines' seat capacity in China than in Japan and Korea given similar HSR service speed.
3. Supply side influence: Airline fares					
Zhang et al. (2014)	93 routes in China	Route-level quarterly panel data	FGLS with Lerner index, **no** HSR characteristics considered, **no** inter-temporal price discrimination (IPD) considered	DV: airline Lerner index, yield, IV: distance, number of air passengers, number of ailines, population, per capita income, tourism_D, lcc_D, HSR_D, GDP growth, season_D	HSR's presence has 15.5% and 14.6% downward pressure on airline Lerner index and yield.
Bergantino and Capozza (2015a)	67 routes in Italy	Route-level daily panel data	RE-GLS, **no** HSR characteristics considered, IPD considered	DV: air fares; IV: market share, HHI, booking day, holiday_D, lcc_D, route_D, month_D, time_D, stay_D.	Air fares are higher on routes with less competition; air fares reach their minimum closer to departure date on routes where there is greater competition.
Bergantino et al. (2015)	2 routes in Italy	Route-level daily panel data	RE-GLS, **no** HSR characteristics considered, IPD considered	DV: air fares; IV: market share, HSR_D, booking day, peak_D, route_D, carrier_D, month_D.	Air fares are 15.5% lower on the Rome Fiumicino-Milan Linate route, and 29% lower on the Rome Fiumicino-Milan Malpensa route with HSR competition.
Capozza (2016)	67 routes in Italy	Route-level daily panel data	RE-GLS, rail in-vehicle time, egress time and IPD considered	DV: air fares; IV: rail travel time, booking day, interaction between rail travel time and booking day, HHI, peak_D, route_D, month_D, departure_D, return_D, time_D, trip length_D.	A 10% increase in rail travel time allows airlines to increase air fares by 3.9%.

Table 1 lists key ex-post studies of the impact of HSR operation on air transport. In the first part of the table: Clewlow et al. (2014), Li et al. (2019); Zhang et al. (2018), Zhang et al.(2017) and Zhang and Zhang (2016) looked at the influence from demand side - airline passenger volume or turnover. These studies show that HSR has the effect of reducing passenger numbers, particularly on shorter routes and the extent of this is effect is determined by relative frequencies and prices. The second and third parts show supply side influence: air frequencies, seats offered and pricing strategy, which is the focus of our study. Albalate et al. (2015), Jiménez and Betancor (2012) and Dobruszkes et al. (2014) studied the impact of HSR on airline traffic in Europe. Wan et al. (2016) adopted a Difference-in-Differences approach to quantify the substitution effects of HSR on air travel in East Asia.

We have found four papers concerning pricing. Zhang et al. (2014) incorporated HSR in measuring the competition in the Chinese airline industry using quarterly panel data to analyse the impact of several factors on yield. Bergantino and Capozza (2015a) explored the impact of HSR competition on air fares using daily panel data on 67 routes in the Italian domestic airline market. Bergantino et al. (2015) studied inter-modal competition on the Rome Fiumicino-Milan Linate route and the Rome Fiumicino-Milan Malpensa route respectively using daily panel data. These studies all identify a negative impact of HSR on air prices. Capozza (2016) focused on measuring the impact of HSR travel time on air pricing policies using daily panel data on the same routes as Bergantino and Capozza (2015a) and found higher air prices are associated with longer HSR travel times.

As most of the highlighted studies only treated HSR as dummy variables, attributes such as HSR service levels and travel time are largely neglected. Although Dobruszkes et al. (2014) did include service level and travel time measures in their study, we believe this introduces another potential problem. Game theory suggests that in situations of limited competition, firms will select their output, i.e. service level, based on observed or anticipated levels of output of their competitors. Thus, there is an endogeneity problem here between HSR frequency and air frequency which has not been addressed in the literature, leading to potentially biased results.

In modelling air frequency we address this endogeneity problem between HSR frequency and air frequency. To this end we incorporate two instrumental variables, namely years of operation of the HSR route and number of stations along the HSR route section, which we consider to be exogenous to air frequency but explanatory variables in terms of HSR frequency. In this way we can identify the impact of HSR frequency on air frequency purged of simultaneity bias.

Those studies which considered HSR travel times (Capozza, 2016; Clewlow et al., 2014; Dobruszkes et al., 2014; Zhang et al., 2017) haven't considered total travel time (ie including access/egress/boarding elements). The difference in total travel time between transport modes gives one a competitive advantage over another. Relative measures of travel time ratio and frequency ratio can reflect these advantages. This is another aspect we address in our modelling.

Yield management is the major method air companies adopt to extract consumer surplus (Bergantino and Capozza, 2011; Stokey, 1979), so it is clearly important to understand HSR's influence on airline's IPD strategies. Three of the four pricing studies known to the authors considered the IPD effect in the Italian market. Table 1 shows the previous studies are mainly related to European markets, whilst studies on the Chinese market, the world's fastest growing HSR market, are rare and those that exist do not specify the competing HSR offer in any detail.

In this paper, we examine how air fare and frequency change in the presence of HSR services in China. In order to conduct our analysis we construct and use a unique database for 15 city pairs whose distances range from 388 km to 1891 km. Air fare and frequency for these city pairs are retrieved and recorded from Qunar (the most popular air ticket booking website in China) every day starting at 30 booking days before flight departure. HSR fare and frequency are recorded from the railway's website (www.12306.cn). We first explore how the presence of HSR and modal service characteristics, such as frequency and total journey time, affect air fares. Then by comparing the effects of booking day and distance on air fares for routes with and without HSR competition, the impact of HSR services on the distribution of air fares over time and distance are analysed. In the second set of analyses, we measure the impact of HSR presence and modal service characteristics on air frequencies.

In summary there are a number of novel aspects to this study. In terms of its application, this is the first paper to look at the impact of HSR competition on both air fares and frequency. In terms of its methodology this is the first work of its kind to address the endogeneity problem between HSR frequency and air frequency. Further, this is the first econometric analysis of the impact of HSR on air transport time-varying fares and frequencies, clearly specifying relative travel times and frequencies between modes as a measure of attractiveness.

The rest of this paper is organised as follows: Section 2 gives a brief background of how prices and frequencies for air and HSR are regulated in China, describes the data and collection procedure. Section 3 presents the econometric model and specifies the variables. Section 4 presents and analyses the regression results. Section 5 draws conclusions.

2. Background, data collection and variables

2.1 Pricing and frequency of air transport and HSR in China

In order for international readers to have a better understanding of the Chinese air and HSR market, and also this paper, we illustrate how prices and frequencies for air and HSR are regulated in China.

Price of air: The baseline airfare in China is specified by the No.107 [2014] CAAC document (CAAC and NDRC, 2014). It is calculated by: $\text{Baseprice} = \log(150, \text{distance} \times 0.6) \times \text{distance} \times 1.1$ (CNY). The airfare varies within limitations: the ticket price cannot exceed 25% of the baseline price, and there is no low-price limit. Airlines usually adjust their ticket price using a yield management system based on time of departure and booking.

Pricing in HSR: HSR prices in China do not fluctuate with either departure time nor booking time. HSR price can be roughly calculated by: $\text{HSRprice} = \text{baseprice}/\text{km} \times \text{distance}$, although railway companies can adjust the price according to local circumstances. At the time our data was collected, the base price for 1st class ticket of high-speed train was 0.74 CNY/km (≈ 0.09 GBP/km); a 2nd class ticket of high-speed train 0.46 CNY/km (≈ 0.05 GBP/km).

Frequency of air transport: A mid-term frequency plan is set up twice every year: summer-autumn and winter-spring. The air frequency coordinators in airlines adjust the frequency on a rolling basis based on the mid-term frequency plan, number of tickets sold, passenger load factor last week, frequency of other airlines on the same route and the weather: thus, the frequency in air transport is more demand driven.

Frequency of HSR: The nationwide railway operation timetable is irregularly revised (6 times in 2013; 8 times in 2014; 10 times in 2015; 8 times in 2016). It determines the train routes and their frequencies which satisfy the spatial distribution of O-D demand.

2.2 Data collection

Fare and frequency of air transport are obtained from the air ticket booking website Qunar (https://www.qunar.com/) which is the most popular website for air ticket booking in China. HSR fare and frequency data are collected from the official national railway's website (http://www.12306.cn).

A web spider was developed by the authors to retrieve air ticket information starting 30 booking days before departure between March 22nd 2016 and July 28th 2016, including carrier name, flight no., plane type, in-journey time, departure time, landing time, departure airport, landing airport and also the lowest ticket prices in economy class of the flight shown on the webpage for that day. Only one-way airfares are recorded, since the price of round-trip tickets for these routes are the same as the sum of two separate one-way tickets[§]. Round-trips between 15 city pairs are selected as the study samples in this paper which are distributed across different areas of China and cover short, middle and long distance of routes both with and without HSR competition (shown in Fig. 1). The samples are representative of the competition

[§] This was confirmed by the authors in the ticket booking websites and official websites of airlines. We also interviewed employees from China's "Big 3" companies, they told us that discounted round trip tickets are rarely provided except for some special occasions in China. Thus the pricing strategy for Chinese airlines in domestic air market is quite different from European countries (Capozza, 2016).

between air transport and HSR in China. A round-trip is treated as two different routes, thus there exist 30 routes in our research, of which 20 routes have HSR competition. Table 2 summarises the main features for 15 city pairs, whose direct distances range from 388km to 1891km.

Fig. 1 Round-trips between 15 city pairs studied in this paper. Source: authors' elaboration

Table 2 Summary of the characteristics of the selected city pairs

City pairs	Distance (km)		In-vehicle time (min)			Average daily frequency	
	Direct	HSR	Air	HSR		Air	HSR
				Fastest	Average		
City pairs with HSR competition							
Shenzhen-Xiamen	465	502	80	191	240	2	34
Beijing-Taiyuan	404	511	80	156	180	6	17
Beijing-Shenyang	628	679	95	240	275	9	28
Guangzhou-Changsha	569	707	80	139	160	4	60
Dalian-Haerbin	867	921	95	215	270	1	18
Hangzhou-Changsha	737	927	110	216	270	5	37
Beijing-Nanjing	899	1032	120	219	270	11	49
Wuhan-Guangzhou	838	1069	110	218	240	10	60
Beijing-Shanghai	1069	1318	130	288	330	51	34
Beijing-Guangzhou	1891	2294	200	557	600	31	5

City pairs without HSR competition			
Xishuangbanna-Kunming	388	70	36
Lanzhou-Chengdu	602	95	7
Chengdu-Kunming	655	95	19
Changsha-Kunming	1073	120	11
Beijing-Lanzhou	1182	155	15

Yield management is a common strategy adopted by airlines to maximize profit. It results in time-varying airfares for a flight which changes over the number of booking days ahead of departure which is a form of IPD in order to segment the market into groups of consumers with different demand elasticities. Our dataset captures the dynamic airfare up to 30 days before departure. Fig.2 shows how the airfare changes for flight CA1503, which operates between Beijing and Nanjing. It decreases almost monotonically as the departure day approaches, and then rise sharply from 7 days ahead of departure onwards.

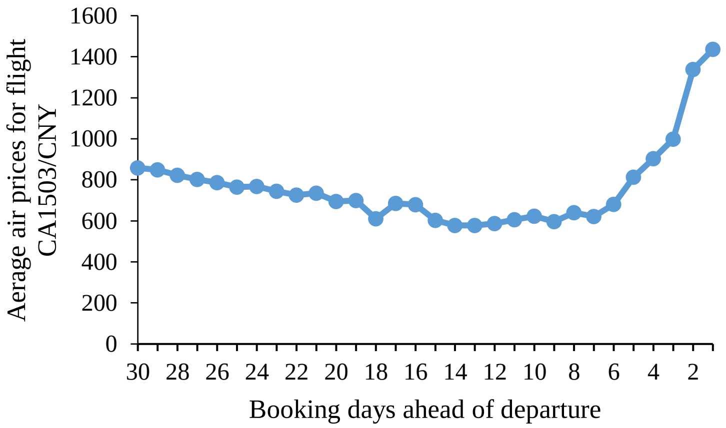

Fig. 2 Airfare changes with different days of booking tickets in advance for flight CA1503

Apart from in-vehicle time, considerable time is spent on access to the trunk leg of the journey. Thus, the total travel time is considered in the paper which is the sum of access time, boarding time, in-vehicle time, and egress time. The average access and egress time between the city centre and the airport or HSR station by private transport are recorded separately using Google Maps. Boarding time for air transport is set to be 60 minutes, as checking-in services are stopped at 45 minutes before departure in most Chinese airports. Boarding time for HSR is 30 minutes which leaves passengers enough time for security checking and boarding. Relative air travel time is defined as the ratio of total travel time by air and HSR. Details of the calculation are shown in Appendix 1.

2.3 Variables

All independent variables are classified into six groups as shown in Table 3: HSR service, route-level attributes, characteristics of the cities, inter-temporal price discrimination (IPD) effects, peak effects and carrier dummies. HSR price is not included as an independent variable given the ticket price of HSR in China is set at a fixed rate (0.05 GBP/km) based on distance which is already considered in the model.

Table 3: Variable descriptions

Category	Variable name	Description	Expected sign

			Pricing Models 1 and 2	Frequency Model 3 and 4
HSR service	HSR	1: has HSR competition; 0: otherwise	-	-
	$\frac{Frequency\_air}{Frequency\_HSR}$	The ratio of daily frequency of airline and frequency of HSR	+	
	$\frac{airtime}{hsrtime}$	The ratio of total travel time by air and by HSR	-	-
	Frequency_HSR	Daily frequency of HSR		unknown
Route attributes	Market share	the share of the daily flights operated by airline j as a proportion of all flights on route i departing on day k	+	
	HHI	the sum of the squared market share for all airlines on route i	+	-
	Distance	Direct distance between each city pair	-	unknown
	$Distance^2$	Squared distance	+	
City characteristics	Population	Sum of the population of the departure and landing city	unknown	+
	Income	Average of per capita annual income in the departure and landing city	+	+
	Connect_city	Number of cities connected by direct flight to the departure city	-	+
IPD	Bookday	number of days of booking in advance, ranging from 1-30	-	
	$Bookday^2$	squared Bookday	+	
Peak effects	Timeslot_dummy	slot 1:0:01-7:00 (base group)		
		slot 2: 7:01-9:00	+	
		slot 3: 9:01-11:00	-	
		slot 4: 11:01-13:00	-	
		slot 5: 13:01-15:00	-	
		slot 6: 15:01-17:00	-	
		slot 7: 17:01-19:00	-	
		slot 8: 19:01-21:00	+	
		slot 9: 21:01-24:00	-	
	Weekday_dummy	Monday (base group)		
		Tuesday	unknown	unknown
		Wednesday	unknown	unknown
		Thursday	unknown	unknown
		Friday	+	+
		Saturday	-	unknown
		Sunday	-	unknown
Carrier	Carrier_dummy	MU: China Eastern Airlines	+	+
		CZ: China Southern Airlines	+	+
		CA: Air China	+	+
		Other airline companies (base group)		

3. Econometric models

3.1 Empirical study on price

To determine how the presence of HSR services affects the airline pricing behaviour, we adopt the following 2 regression models[**] which model airfare as a function of a range of attributes associated with HSR, route, city, booking day, peak and the air carrier. Model 1 measures the impact of the opening of HSR services on airfare and our main objective here is to observe the behaviour of the variable HSR dummy. The model used data from routes both with and without HSR competition. It can also be used to compare with similar studies in other regions. Model 2 aims to analyse how relative frequency and journey time influence the price per kilometre for the subset of routes with HSR competition. We also use Model 2 to compare the differences between routes with and without HSR competition.

Model 1:

$$\begin{aligned} Priceperkm_{ijkmt}, \\ &= \beta_0 + \beta_1 HSR_i + \beta_2 HSR_i * \frac{Frequency\_air}{Frequency\_HSR}_i + \beta_3 Market\_share_{ijk} + \beta_4 HHI_{ik} \\ &+ \beta_5 Distance_i + \beta_6 Distance_i^2 + \beta_7 Population_i + \beta_8 Income_i \\ &+ \beta_9 Connect\_city_i + \beta_{10} Bookday_t + \beta_{11} Bookday_t^2 \\ &+ \sum_{s=2}^{9} \beta_{12,s} Timeslot\_dummy_{ikm,s} + \sum_{w=2}^{7} \beta_{13,w} Weekday\_dummy_{km,w} \\ &+ \sum_{c=1}^{3} \beta_{14,c} Carrier\_dummy_{j,c} + u_{ijkmt} \qquad (1) \end{aligned}$$

Model 2:

$$\begin{aligned} Priceperkm_{ijkmt} \\ &= \beta_0 + \beta_1 \frac{Frequency\_air}{Frequency\_HSR}_i + \beta_2 \frac{airtime}{hsrtime_i} + \beta_3 Market\_share_{ijk} + \beta_4 HHI_{ik} \\ &+ \beta_5 Distance_i + \beta_6 {Distance_i}^2 + \beta_7 Population_i + \beta_8 Income_i \\ &+ \beta_9 Connect\_city_i + \beta_{10} Bookday_t + \beta_{11} Bookday_t^2 \\ &+ \sum_{s=2}^{9} \beta_{12,s} Timeslot\_dummy_{ikm,s} + \sum_{w=2}^{7} \beta_{13,w} Weekday\_dummy_{km,w} \\ &+ \sum_{c=1}^{3} \beta_{14,c} Carrier\_dummy_{j,c} + u_{ijkmt} \qquad (2) \end{aligned}$$

The dependent variable $Priceperkm$ measures the airfare of the observed flight m on a given route i operated by carrier j for the departure date k collected t days (1-30) before departure, divided by route distance so as to obtain the price per kilometre, which normalises fare across different journey lengths (Dresner et al., 1996; Fischer and Kamerschen, 2003).

[**] We have compared the fit of linear form model versus log-log form model using the method developed by (Weisberg 2005), the linear model fits better for the price competition datasets, thus we opt for the linear price competition model in this paper.

We use the HSR dummy to see how the presence of HSR affects airfare. It takes value of 1 if a given route of air transport is in direct competition with an HSR service, and 0 otherwise.

The other two variables $airtime/hsrtime$ and $Frequency\_air/Frequency\_HSR$ are important factors affecting the intermodal competition, which, to the best of our knowledge, are first adopted in this paper to show how HSR services affect airfare. We calculate the total travel time as the sum of access, egress time, boarding, secure check-in time and in-vehicle time (the calculation is shown in Appendix 1). The variable $airtime/hsrtime$ takes the value of the air total travel time divided by HSR total travel time on a given route. The other variable, $Frequency\_air/Frequency\_HSR$ takes the value of daily air frequencies divided by daily HSR frequencies. To control for the influence of relative frequency on air pricing in Model 1, we incorporate the interaction of HSR dummy with $Frequency\_air/Frequency\_HSR$.

The variable $Market\_share_{ijk}$ is the share of the daily flights operated by an airline company j on route i departing on day k. It captures the degree of an airline's market power on a given route relative to other airlines. The variable HHI is the sum of the squared market share for all the airlines on route i. It measures the concentration level on a given route. $Population$ comprises the sum of the population of the departure and landing cities: it represents the potential demand available on a given route. GDP or per capita income are factors mostly included to show the level of economic development of a city. The variable $Connect\_city$ denotes how many cities are connected to the departure city's airport by direct flights, which will reflect the hub status of a given city's airport. The variable $Bookday$ is incorporated to measure the IPD effect on airfares (Stokey, 1979). $Timeslot\_dummy$ divides the whole day of 24 hours into 9 slots (the time slot specification can be found in Table 3), with slot 1 (00:00-7:00) being the omitted base category. $Weekday\_dummy$ indicates the day of a week, with Monday being the base category. $Carrier\_dummy$ is also included to capture the differences in fares among the 3 biggest airline companies, with CA standing for Air China, CZ for China Southern Airlines, MU for China Eastern Airlines, and the other carriers being the base category.

3.2 Empirical study on frequency

The following equations[††] are adopted to analyse the impact of HSR on air service frequencies. Analogous to Model 1, Model 3 uses the full dataset to compare routes with and without HSR competition; analogous to Model 2, Model 4 only analyses the subset of routes with HSR competition to see how HSR frequencies and $airtime/hsrtime$ influence air service frequencies:

Model 3:

$$\begin{aligned}\ln(Frequency\_air_{ik}) &= \alpha_0 + \alpha_1 HSR_i + \alpha_2 \ln(Distance_i) + \alpha_3 HHI_{ik} + \alpha_4 \ln(Population_i) \\ &+ \alpha_5 \ln(Income_i) + \alpha_6 \ln(Connect_{city_i}) \\ &+ \sum_{w=2}^{7} \beta_{6,w}\, Weekday\_dummy_{ik,w} + \sum_{c=1}^{3} \beta_{7,c} Carrier\_dummy_{ik,c} + \epsilon_{ik} \quad (3)\end{aligned}$$

Model 4:

[††] We have compared the fit of linear form model versus log-log form model using the method developed by (Weisberg 2005); the log-log model fits better for the frequency competition datasets, thus we opt for the log-log frequency competition model in this paper.

$$
\begin{aligned}
\ln(\,Frequency\_air_{ik})& \\
&= \alpha_0 + \alpha_1 \ln(Frequency\_HSR_i) + \alpha_2 \ln\left(\frac{airtime}{hsrtime_i}\right) + \alpha_3 \ln(Distance_i) \\
&+ \alpha_4 HHI_{ik} + \alpha_5 \ln(Population_i) + \alpha_6 \ln(Income_i) + \alpha_7 \ln(Connect\_city_i) \\
&+ \sum_{w=2}^{7} \beta_{8,w}\, Weekday\_dummy_{ik,w} + \sum_{c=1}^{3} \beta_{9,c} Carrier\_dummy_{ik,c} + \epsilon_{ik} \qquad (4)
\end{aligned}
$$

where the dependent variable is the log of frequency of air service for route i on the departure day of k. The following groups of independent variables are considered: HSR service, route attributes, city characteristics, day of week and carrier dummies (see Table 3).

We take into account the endogeneity issue in Model 4: as has been discussed in section 3, air and rail will adjust their frequency strategically, i.e. airlines may consider HSR frequency in setting their own frequency, and vice versa. This can lead to correlation between HSR frequency and the error term in Model 4 and a biased coefficient on HSR frequency. To control for this endogeneity, we undertake a two-stage instrumental variable approach which involves identifying variables which influence HSR frequency but not air frequency. These variables are used in a first stage regression to explain HSR frequency. In the second stage regression explaining Air frequency, HSR frequency is replaced by the predicted values from the first stage regression.

We identified two candidate instrumental variables: $ln\ (stop)$ and $ln(lineyear)$. $stop$ captures the number of stops on this route; unlike air services serving just a dedicated OD pair, rail serves all stops along the routes. There will be more midway passengers if a train stops at more stations, thus the rail service level for a particular OD might well be positively influenced by the number of other stops served on the route but this would have no direct influence on air frequencies. $lineyear$ shows how many years this HSR route has operated. Given time, HSR can become better connected to local transport networks: the rail network effect will be better achieved, and business districts will develop around HSR stations after several years of operation thus passenger volume will grow. We expect those routes with more years of operation to have higher HSR frequencies.

On routes with slower relative air travel times ($airtime/hsrtime$), air companies face more competition from HSR and they may need to increase service frequencies to compete with HSR. However, the demand for air services may be much lower on these routes compared to those with smaller $airtime/hsrtime$. Air companies need to provide more services on routes with higher demand. Overall, we think the demand influence may override the ‘competition’ influence, thus the expected sign for $airtime/hsrtime$ is negative.

4. Results

The parameters in the price competition models (1 and 2) are estimated with panel data comprising 1,499,955 observations of 30 successive days’ air price information before departure on 15 city pairs (30 routes). The parameters in the frequency competition models (3 and 4) are estimated with panel data of 2995 observations on air frequency for different departure days over 30 routes. The panel is unbalanced as some flight fares are posted less than 30 days before departure and some flight tickets are sold out before departure. In order to take into account the time-invariant variables (e.g., HSR dummy, population, distance etc), we use a Random Effects Generalised Least Square (RE-GLS) estimator to estimate the first 3 models.

Regarding model 4, the dependent variable (air frequency) and independent variable (HSR frequency) are interdependent, thus may have endogeneity issues, so we use a two-stage approach (RE-G2SLS) by instrumenting for HSR frequency. The result estimated by a one-stage RE-GLS is also included for comparison. In order to compare the impact of variables on routes with and without HSR services, we re-estimate these models using only data for routes without HSR services, the results of which are included in the appendix.

Table 4 Regression results for pricing competition

	Model 1		Model 2	
Dependent variable	priceperkm(air)		priceperkm(air)	
Variables	All routes		Routes with HSR	
	Coefficients	Std.dev.	Coefficients	Std.dev.
HSR Dummy	-0.397***	0.010		
HSR*(air/HSR frequencies)	0.048***	0.004		
air/HSR frequencies			0.010***	0.000
airtime/hsrtime			-0.512***	0.042
Route market share ‡‡	0.023***	0.001	0.022***	0.001
Route HHI	0.011**	0.002	0.025***	0.002
Distance	-0.241***	0.005	-0.214***	0.004
$Distance^2$	0.007***	0.000	0.006***	0.000
Population	-0.012***	0.001	-0.024	0.074
Income	0.364***	0.009	0.149***	0.009
Connect city	0.053***	0.003	0.177***	0.003
Bookday	-0.013***	0.000	-0.026***	0.000
Bookday^2	0.000***	0.000	0.001***	0.000
Timeslot 2	0.052***	0.007	0.042***	0.013
Timeslot 3	0.073***	0.008	0.100***	0.013
Timeslot 4	0.235***	0.008	0.177***	0.013
Timeslot 5	0.188***	0.008	0.142***	0.013
Timeslot 6	0.187***	0.008	0.170***	0.013
Timeslot 7	0.132***	0.008	0.132***	0.013
Timeslot 8	0.034***	0.007	0.039***	0.013
Timeslot 9	0.043***	0.007	-0.056***	0.013
Tuesday	-0.010*	0.006	0.008	0.006
Wednesday	0.021***	0.006	0.053***	0.006
Thursday	0.030***	0.006	0.055***	0.006
Friday	0.080***	0.006	0.126***	0.006
Saturday	-0.022***	0.006	-0.057***	0.006
Sunday	0.002	0.006	-0.003	0.006
China Southern Airline	0.132***	0.006	0.059***	0.006
China Eastern Airline	0.169***	0.006	-0.067**	0.006
Air China	0.272***	0.005	0.169***	0.005
Cons	1.381***	0.022	1.768***	0.047
Robust Hausman Test	0.921		0.967	
R^2	0.425		0.322	
Observations	1499955		806121	

***Significance levels of 1% **Significance levels of 5%*Significance levels of 10%

Table 5 Regressions results for frequency competition (Model 3)

	Model 3
Dependent variable	ln air-frequency
Variables	All routes

‡‡ Market share is incorporated to show the company's market power on a on a given route relative to other airlines. HHI is incorporated to show the route's concentration level. We checked for multicollinearity using VIF (variance inflation factor). Results show that the VIF value for market share and HHI are 4.72 and 5.30 respectively in Model 1, which means that the collinearity issue between them can be disregarded in the model.

	Coefficients	Std.dev.
HSR Dummy	-0.923***	0.290
ln Distance	0.116	0.273
Route HHI	0.042	0.040
ln Population	0.480*	0.274
ln Income	1.516***	0.811
ln Connect city	0.053	0.163
Tuesday	-0.022***	0.005
Wednesday	0.011**	0.005
Thursday	-0.032***	0.005
Friday	0.008*	0.005
Saturday	-0.029***	0.005
Sunday	-0.016***	0.005
China Southern Airline	-0.002	0.005
China Eastern Airline	-0.004	0.004
Air China	-0.002	0.004
Cons	-17.000**	8.179
Robust Hausman Test	0.815	
R^2	0.289	
Observations	2995	

***Significance levels of 1% **Significance levels of 5%*Significance levels of 10%

Table 6 Regressions results for frequency competition (Model 4)

Model 4 Routes with HSR						
Dependent variable	ln(air-frequency)		ln(HSR-frequency)		ln(air-frequency)	
Variables	RE GLS		RE G2SLS-**first stage**		RE G2SLS-**second stage**	
	Coefficients	Std.dev.	Coefficients	Std.dev.	Coefficients	Std.dev.
ln HSR frequency	-0.017**	0.008			-0.072***	0.009
(ln lineyear) iv[§§]			1.261***	0.008		
(ln stop) iv			6.243***	0.043		
ln airtime/hsrtime	-1.355***	0.059	13.914***	0.071	-1.093***	0.06
ln Distance	-0.317***	0.019	4.547***	0.029	-0.299***	0.019
Route HHI	-0.653***	0.022	1.038***	0.016	-0.671***	0.022
ln Population	1.276***	0.016	0.282***	0.013	1.258***	0.017
ln Income	2.499***	0.045	3.070***	0.029	2.562***	0.046
ln Connect city	0.041***	0.008	0.028***	0.005	0.044***	0.008
Tuesday	-0.021	0.014	-0.003	0.008	-0.021	0.014
Wednesday	0.011	0.014	-0.004	0.008	0.011	0.014
Thursday	-0.030**	0.014	-0.007	0.008	-0.031**	0.014
Friday	0.006	0.014	-0.005	0.008	0.006	0.014
Saturday	-0.029**	0.014	-0.012	0.008	-0.029**	0.015
Sunday	-0.028*	0.015	-0.013	0.008	-0.028*	0.015
China Southern Airline	0.015	0.013	-0.001	0.009	-0.019	0.013
China Eastern Airline	0.090***	0.014	0.104***	0.008	0.079***	0.014
Air China	-0.054***	0.013	0.007	0.008	-0.062***	0.013
Cons	-31.310***	0.483	-86.751***	0.63	-31.680***	0.488
Robust Hausman Test	0.897				0.895	
R^2	0.944				0.943	

[§§] Instrumental variables for HSR frequency. The p value for Sargan Hansen statistic is 0.996, which means we cannot reject the null hypothesis that over-identifying restrictions are valid, in other words, these two variables do not have over-identification issues: they are valid instrumental variables. The Cragg-Donald Wald F value is 20550.17, much bigger than 10% maximal IV size (19.93). This test statistic rejects the null hypothesis that the equation is weakly identified, in other words, the instrumental variables are strong.

Observations	1971	1971

***Significance levels of 1% **Significance levels of 5%*Significance levels of 10%

Table 4 reports the regression results for the pricing competition models. Holding other variables constant, price per km on routes with HSR competition are 0.397 CNY lower than routes without HSR competition. As the average air price per km for routes without HSR in this sample is 1.16 CNY, this amounts to a 34.2% reduction in the ticket price. This indicates that the presence of HSR services exerts strong downward pressure on air pricing. In Model 1 and Model 2, airfares are higher on routes with higher air-frequency/HSR-frequency: this means that running more services can give air a competitive advantage over HSR services, thus leaving air more scope to raise price.

Table 5 shows the results from Model 3 where frequencies on routes with HSR competition are 60.2% less than routes without HSR competition.

Table 6 shows the results for frequency Model 4 featuring HSR routes: the left column gives the regression result using RE-GLS, the other two columns display the two stages of the result estimated by RE-G2SLS, ie the instrumental variable approach. Comparing the leftmost and rightmost columns in Table 6, we can see that except for the increase for the parameter value of ln HSR_frequency and a slight drop for the parameter value of ln airtime/hsrtime, the values for the other parameters are very similar. This result confirms our assumption in section 3.2.1 that air frequency and HSR frequency have endogeneity issues and the coefficient on HSR frequency becomes more negative and significant under IV, suggesting that straight-forward OLS estimates of the impact of HSR frequencies could be biased upwards.

The dependent variable for the middle column of Table 6 , which shows the result for the first stage of RE-G2SLS, is HSR frequency. The instrumental variables $lineyear$ and $stop$ are positively and significantly related to HSR frequency. Routes in use for longer periods have higher HSR frequencies than newly opened ones. Routes linking more stops also have higher HSR frequencies while controlling for distance as expected.

From the rightmost column in Table 6, we see air frequency is negatively related to HSR frequency: higher-frequency HSR service can lead to decreased air demand, thus causing air to lower its frequency. This result contradicts Dobruszkes et al. (2014) who find HSR frequency is positively related to air frequency in EU; they originally assumed the sign would be negative but suggested that this contradiction might be caused by the high correlation between HSR travel time and HSR frequency in their model. We consider they may also have neglected the endogeneity problem between air frequency and rail frequency. The results displayed in Table 6 show that RE-G2SLS fits better in Model 4 than RE-GLS.

At the foot of each results table, we report the Robust Hausman specification error test. In each case these do not lead to the rejection of the null hypothesis that the RE GLS estimator is consistent and thus suggest the specification is preferred over Fixed Effects due to its higher efficiency (Wooldridge, 2002).

The $airtime/hsrtime$ variable presents the expected negative sign in Model 2 and Model 4. A smaller $airtime/hsrtime$ ratio means HSR loses its time advantage over air, thus more passengers will opt for air, airlines can charge more for passengers and air frequencies will rise on those routes.

$Market\_share$ exerts a positive influence on air fares: from Model 1 we see a 1% increase in market share for an airline company will lead to 0.023 CNY higher price per km. The coefficient on HHI indicates a positive influence on fares (Models 1 and 2) and a negative influence on frequencies (Models 3 and 4), which means more concentrated air markets in China will have higher fares and lower air service frequencies.

The coefficients associated with $Distance$ and $Distance^2$ present the expected sign for Model 1 and Model 2 which means airline companies will post lower (per km) fares with distance on shorter-and middle-distance routes due to average cost reductions, and post slightly higher prices on long-distance routes on account of lack of competition. When calculating the marginal effect of distance on fares, the turning point for routes with HSR competition is at 1443 km, while the minimum of the curve shifts leftwards for routes without HSR competition (1011 km). As Fu et al. (2012) show, HSR in China can be competitive for air for city pairs up to 1200 km apart; a later turning point on routes with HSR competition implies the appearance of HSR can put pressure on air companies to keep low fares for longer distances.. The results for Model 4 regarding distance variables show a negative sign, meaning air frequencies will be lower on longer routes.

$Population$ is negatively related to price: one explanation may be a larger population can generate higher demand and help air companies to save cost through scale economies. $Income_i$ has the expected positive sign for Model 1 and Model 2: this shows that air companies price higher for city pairs with higher incomes. For Model 3 and Model 4, both population and income have the expected positive sign, since larger population and higher income levels spur higher demand, triggering a supply response.

$Connect\_city$ shows a positive sign for Model 2 and Model 4, which means that airports facing HSR competition with more connected cities have higher passenger demand, allowing air companies to price higher and run higher frequencies.

The $Bookday$ and $Bookday^2$ variables have the expected sign and are both highly significant in the pricing models, which means that the relationship between booking day and price per km is non-monotonic. The marginal effect of Bookday on fares is calculated by:

$$\frac{\partial Priceperkm_{ijkmt}}{\partial Bookday_t} = \gamma_1 + 2\gamma_2 Bookday_t \tag{5}$$

where γ_1 denotes the coefficient of $Bookday_t$ and γ_2 denotes the coefficient of $Bookday_t^2$. We found that the minimum fare for routes with HSR competition occurs 19-20 days before departure; the minimum of the curve shifts leftwards (ie occurs earlier) for routes without HSR competition (24 days). There is a 4-5 day difference, implying that the decreasing part of the fare inter-temporal profile is longer for routes with an alternative to air travel. This shows that HSR competition not only influences average air prices, but also the price distribution over time.

The coefficients associated with $Carrier\_dummy$ show that, all else equal, Air China charges the highest prices, while China Southern Airline charges more than other small air companies on all routes. Comparing Model 2 and the comparison model we can see that the price difference between the "Big 3" and other small air companies is less on routes with HSR competition: the average fare for China Eastern Airline is even lower than other companies in Model 2.

5. Conclusions and discussions

This paper offers the first empirical analysis to assess whether the introduction of HSR services influences air ticket pricing and flight frequency in China. We conducted an ex-post analysis covering 15 city pairs whose direct distances range from 388 km to 1891 km, using data obtained from the ticket booking website (Qunar). To the best knowledge of the authors, this is the first research regarding two key aspects of intermodal competition that should be considered in conjunction to fully assess strategic response behaviour: pricing and frequency. This is also the first work to deal with the endogeneity issue between the modal frequencies, addressed through the use of use instrumental variables. In these aspects this work represents a clear contribution to the research on HSR-air competition for all countries which have HSR or are about to build HSR.

Our empirical analysis confirms that airlines in China do offer lower fares against the competition of HSR, and the influence is relatively strong compared with European market (Albalate et al., 2015; Bergantino et al., 2015). We find higher airfares are associated with higher relative frequency of air transport. Airlines also provide fewer services on routes with higher HSR frequencies. We found that the IPD of fares can be shaped by inter-modal competition. The J-curve for airfares is more pronounced and its minimum value occurs earlier before departure for routes without HSR competition. The results provide evidence that airlines on routes with HSR services have less monopoly power with associated indirect benefits for air travellers in terms of choice and fares. However, if competition is to flourish, it may require less regulation in these markets. Policy makers may take this indirect benefit into account when undertaking a cost-benefit analysis for new HSR routes.

We also find that relative travel time has a strong influence on airfares and frequencies: when the relative travel time for air transport is higher, both airfares and frequencies decrease greatly. In addition, the punctuality rate for Chinese air carriers is among the lowest in the world (Wang Ying, 2015). The unreliable travel time is not conducive to attracting travellers when competing with the rapidly growing HSR network. This can be largely ascribed to the strict airspace control: 80% of China's national airspace is devoted to military use. Loosening this airspace control could help to solve the air route capacity issue, improving the punctuality rate for airlines and attracting more travellers.

Another way to improve the service of air transport is to provide an affordable service and maintain the high time efficiency, i.e. develop the low-cost carrier (LCC) market. The experience in Europe has shown that LCC is an effective means to increase air traffic when facing competition from HSR (Clewlow et al., 2014). As the domestic air market is dominated by the 'Big 3' state-owned airlines whose total market share is 80% (Zhang et al., 2014) , there is very little space for the LCC market to develop in China. What's more, as the Chinese air transport market is highly regulated, LCCs cannot obtain administrative approval to run those profitable mainlines. The slot allocation system is opaque, which leads to corruption and stifled the growth of LCCs (Wang et al., 2018). Further policy interventions should favour the development of LCCs.

Our findings suggest that inter-modal competition can force airlines to keep low fares for a longer distance trip. Faced with fierce competition in the medium-distance market, airlines should consider concentrating on the long-distance and international markets to avoid head-to-head competition with HSR. Airlines can develop hub-and-spoke networks to combine traffic from city-pairs without HSR services to hub airports, and transfer them to long-distance routes, which hasn't been undertaken by most Chinese airlines (Fu et al., 2012; Goldman Sachs, 2010). The longer-term viability of HS strategy has been justified by Jiang and Zhang (2016).

'Hub-and-track' strategy is another strategy option. Airlines can cut services on routes with HSR and focus on the more profitable long-distance and international routes. As most major airports in China are experiencing capacity shortages (Fu et al., 2012), the integration between air and rail transport can improve welfare (Jiang and Zhang, 2014; Xia and Zhang, 2016). On-site HSR stations like Paris-CDG and Frankfurt are good examples of this integration. Now 9 airports in China (Shanghai Hongqiao, Changchun Longjia, Haikou Meilan, Shijiazhuang Zhengding, Chengdu Shuangliu, Guiyang Longdongbao, Lanzhou Zhongchuan, Zhengzhou Xinzheng and Sanya Phoenix) have on-site HSR stations, and China Eastern and Spring Airlines have provided integrated air-rail ticket service. However, this service is only at its initial stage: it is provided on limited routes, tickets are collected separately and passengers need to carry their luggage for the 2nd trip.

Acknowledgements

We are grateful to all anonymous referees of this journal for valuable comments on an earlier draft.

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Appendix

Appendix 1 The details about the calculation of airtime/hsrtime

Routes	Airline (min)					High-speed rail (min)					airtime/hsrtime
	Access time	Boarding time	In-vehicle time	Egress time	Total time	Access time	Boarding time	Average in-vehicle time	Egress time	Total time	
Shenzhen-Xiamen	40	60	80	20	200	20	30	240	30	320	0.63
Xiamen-Shenzhen	20	60	80	40	200	30	30	240	20	320	0.63
Taiyuan-Beijing	30	60	80	35	205	20	30	180	20	250	0.82
Beijing-Taiyuan	35	60	80	30	205	20	30	180	20	250	0.82
Beijing-Shenyang	35	60	95	30	220	20	30	275	6	331	0.66
Shenyang-Beijing	30	60	95	35	220	6	30	275	20	331	0.66
Changsha-Guangzhou	40	60	80	40	220	35	30	160	40	265	0.83
Guangzhou-Changsha	40	60	80	40	220	40	30	160	35	265	0.83
Haerbin-Dalian	40	60	95	20	215	35	30	270	20	355	0.61
Dalian-Haerbin	20	60	95	40	215	20	30	270	35	355	0.61
Hangzhou-Changsha	35	60	110	40	245	15	30	270	35	350	0.7
Changsha-Hangzhou	40	60	110	35	245	35	30	270	15	350	0.7
Beijing-Nanjing	35	60	120	40	255	20	30	270	20	340	0.75
Nanjing-Beijing	40	60	120	35	255	20	30	270	20	340	0.75
Wuhan-Guangzhou	30	60	110	50	250	25	30	240	40	335	0.75
Guangzhou-Wuhan	50	60	110	30	250	40	30	240	25	335	0.75
Beijing-Shanghai	35	60	130	30	255	20	30	330	30	410	0.62
Shanghai-Beijing	30	60	130	35	255	30	30	330	20	410	0.62
Beijing-Guangzhou	35	60	200	50	345	20	30	600	40	690	0.5
Guangzhou-Beijing	50	60	200	35	345	40	30	600	20	690	0.5

Appendix 2 Comparison model

Pricing competition comparison model (routes without HSR)		
Dependent variable	priceperkm(air)	
Variables	Coefficients	Std.dev.
Route market share	0.010	0.002
Route HHI	0.020***	0.003
Distance	-0.603***	0.016
$Distance^2$	0.030***	0.001
Population	-1.342***	0.136
Income	0.297***	0.033
Connect city	-0.044***	0.004
Bookday	-0.008***	0.000
Bookday^2	0.000***	0.000
Timeslot 2	0.103***	0.009
Timeslot 3	0.178***	0.011
Timeslot 4	0.372***	0.011
Timeslot 5	0.339***	0.013
Timeslot 6	0.344***	0.012
Timeslot 7	0.276***	0.011
Timeslot 8	0.083***	0.010
Timeslot 9	0.064***	0.008
Tuesday	-0.052***	0.009
Wednesday	-0.020**	0.009
Thursday	-0.023**	0.009
Friday	0.034***	0.009
Saturday	-0.003	0.009
Sunday	-0.001	0.009
China Southern Airline	0.190***	0.017
China Eastern Airline	0.494***	0.012
Air China	0.453***	0.013
Cons	2.090***	0.083
R^2	0.488	
Observations	524891	

Pricing competition comparison model (routes without HSR)		
Dependent variable	ln air-frequency	
Variables	Coefficients	Std.dev.
ln Distance	-1.891***	0.045
Route HHI	4.258***	0.207
ln Population	-1.023***	0.026
ln Income	8.324***	0.194
ln Connect city	-0.012	0.010
Tuesday	-0.034	0.022
Wednesday	0.004	0.022
Thursday	-0.035	0.022
Friday	0.021	0.022
Saturday	-0.034	0.023
Sunday	0.020	0.024
China Southern Airline	-0.129***	0.030
China Eastern Airline	0.015	0.014
Air China	0.123***	0.018
Cons	-63.493***	1.700
R^2	0.816	
Observations	1024	