Welfare implications for air passengers in the era of high-speed rail in China

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Abstract

Despite facing the rapid expansion of high-speed rail (HSR) services, China's airline industry has experienced substantial growth in the last decade. Using panel data from 2007 to 2016, this paper assesses the welfare changes for both economy- and business-class air passengers in China due to the HSR entry. We found that the demand for air travel is inelastic and that the HSR entry has led to significant welfare changes for air passengers. Specifically, air passengers in the short-distance markets were worse off, largely driven by a dramatic cut in flight frequency. However, over time, their welfare could improve when flight frequencies were restored. In contrast, in the medium- and long-distance markets, air passengers could be better off immediately after the HSR entry, thanks to the lower airfare and insignificant drop in flight frequency. However, a reduction in welfare was observed in the long run, after airlines gradually reduced the flight frequency.

Keywords: Airline competition; high-speed rail; welfare analysis; business class; economy class

1. Introduction

The Chinese airline industry has continued to experience tremendous growth in the last decade with an average annual growth rate of 10.3% for the passenger market and 7.96% for the cargo market from 2009 to 2018. This growth trend is underpinned by a huge population and rapid economic growth (Zhu et al., 2018). Increasing per capita income has made air transport a more affordable travel mode for many Chinese people. However, a recent report estimates that 70% of Chinese citizens, or one billion people, have never flown in their life (Li, 2019). On the one hand, this may imply that China's air transport still has huge potential. On the other hand, given the relatively small share of air transport among all transport modes, there must be some other good substitutes available to consumers. In fact, the number of business-class passengers stayed relatively stable in the last decade despite the increased flight frequency and capacity in China's airline industry (see Fig. 1). Among all the transport modes, high-speed rail (HSR) is regarded as the best substitute for air transport. The HSR network and traffic in China have experienced rapid growth since the introduction of the first HSR in 2008. By February 2020, China had constructed an HSR network of more than 35,000 km (kilometer), accounting for about 70% of the world's total (UIC, 2020). According to the updated "Medium-to-Long-Term Railway Network Plan" covering the period 2016-2025 with an outlook to 2030, China's HSR network will by 2025 reach a total of 38,000 km. It is planned that by the end of 2020, 192 prefectural-level cities in China will be connected by HSR lines (Xia and Zhang, 2017; Wang et al., 2017; Zhu et al, 2019). The rapid development of HSR has undoubtedly put strong competitive pressure on China's airline industry (Chen, 2017; Ma et al., 2019a; Wang et al., 2017; Wang et al., 2018a, Zhang et al., 2020). Zhang and Zhang (2016) and Chen (2017) found that there was a significant drop in air traffic, flight frequency and seat capacity after the introduction of parallel HSR services. A good survey of the air-rail competition can be found in Zhang et al. (2019).

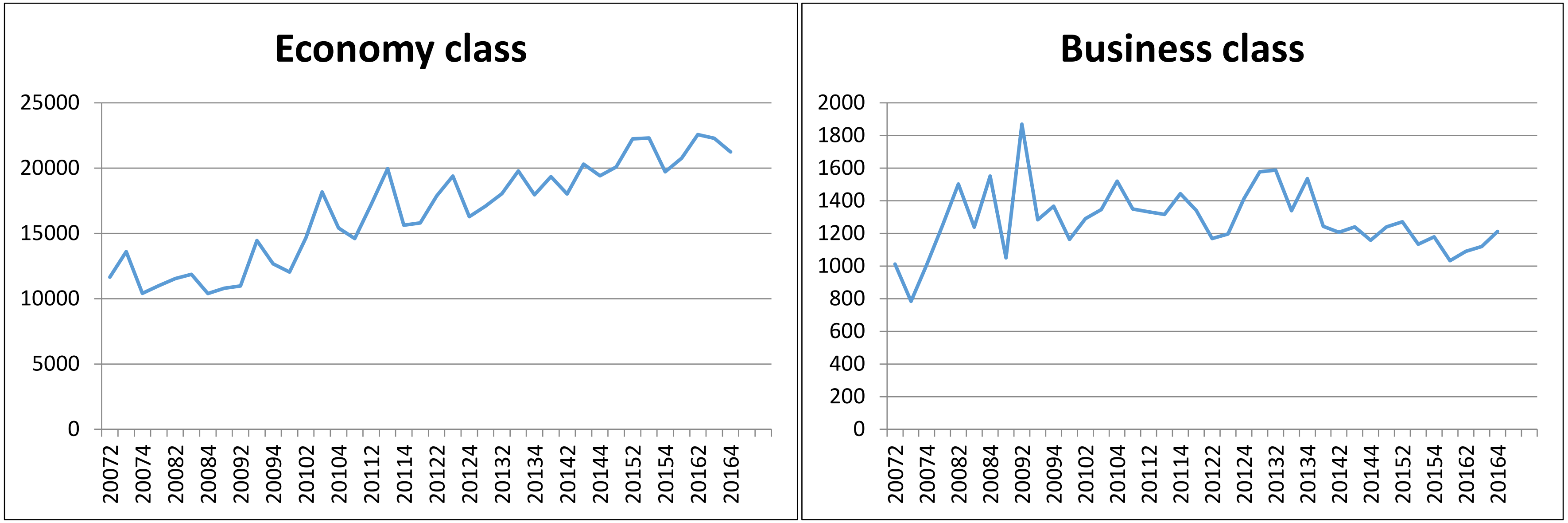

Fig. 1 Average number of passengers carried per route per quarter from 2007-2016

The presence of HSR is expected to have a downward pressure on airfares due to decreasing air travel demand. However, with airlines reducing capacities and/or withdrawing from a market, airfares can maintain at a stable level or even increase. In addition, head-to-head competition between HSR and air could force airlines to engage in tacit collusion on some lucrative routes, which may result in a rise in airfares. Implicit collusion among airlines and air-rail cooperation are the likely reasons resulting in this outcome. Therefore, the impact of HSR on airline prices is unclear. Meanwhile, the flight frequency is also important for air passengers' utility. HSR competition could affect airlines' flight frequency and schedule. Overall, the impact of HSR competition on air passengers' welfare is unknown. Despite rich empirical studies about the impact of HSR competition on airline prices and traffic, to the best of our knowledge, there is a lack of research into the changes of the air passenger welfare, let alone distinguish that between leisure and business passengers, particularly in the aviation market of China. This paper aims to fill this gap.

Following Berry (1994) and Doi and Ohashi (2019), this paper first estimates the airline passenger demand function using the reduced-form BLP model (Berry, Levinsohn, and Pakes, 1995). We estimate the model for both leisure and business passengers, respectively. These estimations are conducted under the assumption that leisure passengers would never buy business-class tickets and business passengers would never buy economy-class tickets. In the Chinese domestic airline market, the assumption is highly likely to hold for the following reasons. First, train services including HSR services in China are well developed connecting almost every large- and medium-sized city, which are good substitutes for air services. Compared with the average level of income, the business-class tickets are still relatively expensive, thus the vast majority of the leisure passengers are unlikely to purchase business-class tickets. Second, in fact, most business-class tickets are paid by a third party such as the employers, rather than the passengers themselves. Therefore, most business passengers seldom buy economy-class tickets either.

To take the impact of HSR into account, we estimate the model with alternative variables related to HSR, such as HSR travel speed and the number of HSR stations. We further split the sample into three categories by route distance—less than 500 km, between 500 and 1,000 km, and longer than 1,000 km. This is because air and HSR exhibit different service substitutability with distance. As suggested by Wang et al. (2018a), airline and HSR are less substitutable on very short-distance (less than 500 km) or long-distance (more than 1,000 km) routes, but compete fiercely on medium-to-long-distance routes (between 500 and 1,000 km). We find that the negative impact of HSR is the strongest on short-distance routes regardless of airline classes.

Specifically, for economy class, as route distance gets longer, the impact of HSR becomes weaker. While for business class, the negative impact of HSR significantly weakens in medium-distance routes, however, it surprisingly rises again in long-distance routes. The results also show that the number of HSR stations, which is a proxy of HSR network coverage, is negatively associated with airlines' market share and the negative effect is stronger for economy-class passengers. Similarly, HSR travel speed is found to negatively affect air transport. We then use the model proposed by McFadden (1978) to calculate consumers' welfare during the study period. We found that: immediately after the HSR entry, air passengers in the short-distance markets are worse off, driven by a dramatic frequency cut. But over time, their welfare in these markets can improve when flights were added back and airfares dropped. In contrast, air passengers in the medium- and long-distance markets can be better off immediately after the HSR entry and enjoy lower airfares. But a reduction in welfare can be observed in the long run, as airlines gradually cut flight frequency, probably because airlines have decided to engage in tacit collusion on these medium- to long-distance routes where they possess stronger market power than HSR.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the model and methodology, followed by the data and the description of variables in Section 4. Section 5 presents the estimation results. Finally, Section 6 concludes the paper.

2. Literature Review

This literature review consists of two parts. The first part reviews the air-HSR competition. The second part concerns the airline demand function estimation and the approaches to calculate air passenger welfare.

2.1. Air-HSR competition

The impact of HSR on airlines has been theoretically and empirically investigated in previous literature. For example, Yang and Zhang (2012) adopted a game-theoretic model to study air-HSR competition, and they showed that HSR competition would reduce airfares and traffic, and the higher the rail speed, the more serious the negative impact. Jiang and Zhang (2016) shed light on the long-term impact of HSR competition on the airline network configuration. They showed that HSR competition can induce airlines to change their network structure from point-to-point to hub-and-spoke to cover more fringe markets. Wang et al. (2018a) modeled the impact of HSR speed on airfares and airline traffic by distinguishing the time and safety effects of HSR speed on airlines. D'Aflonso et al. (2015) analytically examined the environmental implication of the air-HSR competition. They argued that, despite a lower unit emission of HSR, air-HSR competition may not bring lower total emissions. This is because intermodal competition could generate more new transport demand.

Empirically, many studies have proved that HSR entry poses a negative impact on airline demand (e.g., Jimenez and Betancor, 2012; Albalate et al., 2015). It is also found that the attraction of HSR depends on its speed, that is, the higher the speed of HSR, the more passengers would be attracted from airlines to HSR (Clewlow et al., 2014; Dobruszkes et al., 2014; Capozza, 2016; Zhang et al., 2014, 2017; Wang et al., 2018a). In addition to HSR speed, route distance is also an important factor affecting air-HSR competition. There is empirical evidence that HSR is more competitive than air on short-distance routes (Wan et al., 2016; Chen, 2017; Wang et al., 2018a).

In addition, some empirical studies applied discrete choice models to investigate the determining factors of passengers' choices between air and HSR. For example, Park and Ha (2006) used survey data to estimate a logit model. They predicted passengers' choices between the conventional airline service and the newly launched HSR service. The results suggested that access time, fare and frequency all significantly affect consumer's choice. Roman and Martin (2007) did a similar survey on air-HSR competition along the Madrid-Barcelona route. The main variables in their study included travel time, travel cost, frequency, waiting time and delay. They found that travel time is a dominating factor in influencing business passengers' choice but not leisure passengers'. Behrens and Pels (2012) used mixed logit models to investigate the air-HSR competition in the London-Paris passenger market. They also found that the travel time, travel frequency, and access/egress distance to airport and HSR stations could be very important to shape consumer's behavior. On the other hand, fare is the key factor affecting leisure passengers' behavior but not business passengers'.

Despite the above-mentioned rich literature on air-HSR competition, the investigation on the air passenger welfare change is surprisingly lacking. HSR entry is found to reduce airfare but usually accompanied by a decrease in flight frequency. Therefore, the welfare implication for air passengers is unclear. Moreover, such welfare change could vary with route distance due to the change in air-HSR service substitutability. We also expect that the welfare implications of HSR for business and leisure passengers are different.

2.2. Airline demand and welfare analysis

To conduct welfare analysis, one has to estimate a consumer demand function derived from the utility-maximizing specification. The most straightforward approach to specify demand for a set of closely related but not identical products is to build a system of demand equations, and then estimate the parameters of each equation. However, the main challenge is that with a large number of products, there will be too many parameters to estimate. McFadden (1974, 1978) solved this dimensional problem with a logit model by projecting the products onto a space of characteristics. However, its estimation relies on individual-level data, and the price endogeneity is not controlled for. Later, BLP (1995) proposed a random coefficient logit model that can estimate the demand utility function with market-level data. It also deals with the endogeneity of prices.

The BLP model has been widely used in recent airline literature. Berry et al. (2006) adopted the BLP model to estimate a general type of airline competition with differentiated products in the US domestic market. Armantier and Richard (2008) investigated the consumer welfare consequences of the code-share agreement between Continental Airlines and Northwest Airlines using a random coefficient discrete choice model. The model allows consumer heterogeneity in choosing price and flight attributes. Berry and Jia (2010) presented a structural BLP model to estimate the impact of demand and supply changes on profitability in 1999 and 2006 in US domestic airline markets. They found that, compared to 1999, air-travel demand was 8 percent more price-sensitive, and passengers displayed a stronger preference for nonstop flights in 2006. Luo (2015) studied the de-hubbing effect of the Cincinnati airport immediately following the Delta-Northwest merger and its impact on consumer welfare. Ciliberto and Williams (2014) used the BLP model to predict whether different levels of multimarket contact between carriers imply different levels of cooperation in setting fares. By nesting conduct parameters into the model, they found that carriers with little multimarket contact do not cooperate in setting fares. Yan and Winston (2014) used the BLP method to estimate the effect of privatization of Bay Area airports on airline price, traffic, and passenger welfare. Wang et al. (2019) developed a BLP-type airline competition model to estimate the degree of airline competition in China's domestic market.

The BLP model requires tremendous computations. However, by assuming the specific form of error term ε_{ijt}, the BLP model can be converted to a reduced-form linear regression model (Berry, 1994; Peters, 2006; Gayle and Le, 2013; Doi and Ohashi, 2019; Chen and Gayle, 2019). This study adopts the reduced-form BLP model. We will explain how the reduced-form model is derived from the BLP model in Section 3.

With the estimated air passenger utility function, researchers can calculate or simulate the passenger welfare change. There are basically two approaches to do this. One is to model and estimate the airline competition (the supply side) together with the demand function. Then, the welfare change can be evaluated through a counterfactual simulation of the new policy or of the market structure change from the supply side (Berry and Jia, 2010; Yan and Winston, 2014). This approach requires an extremely heavy computational workload and many strong assumptions on market competition behaviors. The second way is to obtain the changes in major airline product characteristics (e.g., airfare, flight frequency), and then put these changes in the estimated utility function to get the welfare change (McFadden, 1978; Small and Rosen, 1981). This approach is more widely employed given its simplicity and no assumption on the supply side. But it can only be applied to ex- post evaluation when we can get the product characteristics changes (Armantier and Richard, 2008; Keating and Rubinfeld, 2013; Vaze et al., 2017). To obtain such changes in product characteristics as a result of policy or market competition structural shocks, some studies adopted the difference-in-differences (DID) approach (Vaze et al., 2017; Doi and Ohashi, 2019), which will also be used in this research.

3. Econometric Model and Identification

3.1. Airline demand model

Before giving the demand model, we first explain some key concepts used in the paper. In our model, a market is defined as an origin-destination (OD) pair of airports and is directional. An itinerary is a flight route linking the origin and destination. In this study, we consider nonstop and one-stop itineraries. There are two reasons for screening out itineraries that contain more than one stop. First, itineraries of more than one stop are very few in the Chinese domestic airline market. Second, our frequency data from IATA is only available for nonstop and one-stop itineraries. A product in a market is defined as an airline-itinerary combination.[1] The specification of the model was used in Berry (1994), Chen and Gayle (2019), Doi and Ohashi (2019) and Choi et al. (2019). The utility of passenger *i* when consuming product j in market *m* at time *t* is given by the following Eq. (1). It is noted that we estimate the utility function for both business- and economy-class passengers.

$$U_{ijmt}=\alpha P_{jmt} + \beta X_{jmt} + \xi_{jmt} + \nu_{imt}(\lambda) + \lambda \varepsilon_{ijmt} \tag{1}$$

[1] The airline-itinerary distinguishes the airline services provided by different airlines on the same OD market. For the same airline, if it provides both direct and one-stop services, these two are regarded as different products as well.

where

- P_{jmt} is the product price,
- X_{jmt} is a vector of product characteristics, including flight frequency, direct or indirect flight, aircraft size, flying distance, and network size of carriers at the endpoint airports. [2]
- α is the marginal disutility of a price increase for passengers.
- β is a vector of coefficients for the product characteristics.
- ξ_{jmt} is the unobserved (to researchers) characteristic of product j.
- ν_{imt} is a "nested logit" random taste that is constant across airline products and differentiates "air travel" from the "outside" good.
- λ is the nested logit parameter that varies between 0 and 1. The closer it approaches 1, the more important the air travel, implying that products within a nest are good substitutes. If λ approaches 0, it means air travel is not different from outside goods and the model becomes a simple logit model.
- ε_{ijmt} is an independently and identically distributed (across products and consumers) "logit error." (BLP imposes assumptions on ε_{ijm} that generates a nested logit structure, where all routes are placed in a single nest but separated from the outside good).

Specifically, conditional on choosing air travel, the percentage of passengers who purchase product j in market *m* in time *t* is given by:

$$\frac{e^{\frac{X_{jmt}\beta - P_{jmt}\alpha + \xi_{jmt}}{\lambda}}}{D_{mt}} \tag{2}$$

where

$$D_{mt} = \sum_{k=1}^{J} e^{(X_{jmt}\beta - P_{jmt}\alpha + \xi_{jmt})/\lambda} \tag{3}$$

[2] Previous studies suggest passengers could have a diminishing marginal utility as flight frequency increases (e.g., Brueckner and Flores-Fillol, 2007), such that a concave function of flight frequency can be adopted. However, this would complicate the estimation and welfare calculation. We thus still use the linear-formed flight frequency, such that the estimated coefficient represents the average marginal utility.

The share of consumers who make a purchase is:

$$s_{mt}\ (x_{mt}, p_{mt}, \xi_{mt}, \theta_d) = \frac{D_{mt}^{\lambda}}{1+D_{mt}^{\lambda}} \tag{4}$$

Given the specific form of error term ε_{ijmt}, the market share for each product in the market can be uniquely identified from a simple algebraic calculation. Denote S_{0mt} as the market share of non-air travel, then:

$$s_{0mt} = \frac{1}{1+D_{mt}^{\lambda}} \tag{5}$$

Then the log of the proportion of product *j* in market *m* in time *t* and no air travel is:

$$\ln\frac{S_{mt}}{S_{0mt}} = \lambda D_{mt} \tag{6}$$

Combining the two expressions yields:

$$\ln\left(\frac{S_{jmt}}{S_{0mt}}\right) = \frac{X_{jmt}\beta - \alpha P_{jmt}}{\lambda} + \left(\frac{1-\lambda}{\lambda}\right)\ln\left(\frac{S_{mt}}{S_0}\right) + \frac{\xi_{jmt}}{\lambda} \tag{7}$$

$$\ln S_{jmt} - \ln S_{0mt} = X_{jmt}\tilde{\beta} - \tilde{\alpha}P_{jmt} + \tilde{\lambda}\ln\left(\frac{S_{mt}}{S_{0mt}}\right) + \tilde{\xi}_{jmt} \tag{8}$$

where $\tilde{\beta} = \frac{\beta}{\lambda}$, $\tilde{\alpha} = \frac{\alpha}{\lambda}$, $\tilde{\lambda} = \frac{1-\lambda}{\lambda}$, and $\tilde{\xi}_{jmt} = \frac{\xi_{jmt}}{\lambda}$. Thus, $\lambda = \frac{1}{1+\tilde{\lambda}}$, $\beta = \frac{\tilde{\beta}}{1+\tilde{\lambda}}$, and $\alpha = \frac{\tilde{\alpha}}{1+\tilde{\lambda}}$.

3.2. Air passenger welfare model

After estimating the passenger utility function coefficients, we are able to calculate the expected values of the per passenger welfare in each market m. The expected value of passenger welfare in a market can be written as the following form in Eq. (9) (McFadden, 1978; Small and Rosen, 1981):

$$\mathrm{E}(CS_{im}) = \mathrm{E}\left[\frac{1}{\alpha^m}\max_{j\in J^m} U_{ijmt}\right] = \mathrm{E}\left[\frac{1}{|\alpha|}\max_{j\in J^m} U_{ijmt}\right] \tag{9}$$

where CS_{im} is the welfare of passenger i in market m. α^m is the marginal utility of money in market *m* (equal to the absolute value of the coefficient of P_{jmt}, $|\alpha|$ in Eq. (1)), U_{ijmt} is the utility of product *j* in market *m* in time *t*, and J^m denotes the set of available of airline products in market m. Small and Rosen (1981) demonstrated that, if all ε_{ijm} are independently and identically distributed and follow the type-I extreme value distribution, then the expected consumer welfare can be expressed as:

$$\mathrm{E}(CS_{im})=\frac{1}{|\alpha|}\ln(\textstyle\sum_{j\in J^m}\exp(U_{ijmt}))+C \qquad (10)$$

where C is an unknown constant which represents the fact that the absolute value of utility cannot be measured. To compare the change in consumer surplus of a specific market in different periods, the following model is used:

$$\Delta\,\mathrm{E}(CS_{im})=\frac{1}{|\alpha|}\left\{\ln\textstyle\sum_{j\in J^{m,period1}}\exp\left(V_j^{m,period1}\right)-\ln\textstyle\sum_{j\in J^{m,period2}}\exp\left(V_j^{m,period2}\right)\right\} \qquad (11)$$

In Section 5, we compare the difference between the $\mathrm{E}(CS_{im})$ values in 2016 and 2009. The reason to select the year 2009 as a benchmark is that the first long-haul HSR was introduced in China in 2009.

4. Data

4.1. Dataset and variables

Our dataset was constructed using information from the IATA Airport Intelligence Services database (AirportIS). The sample selected contains quarterly domestic airline route information on the origin, destination, economy- and business-class airfares and the quarterly number of passengers by routes and carriers, spanning from the first quarter of 2005 to the last quarter of 2016. Based on the Statistical Data on Civil Aviation of China (CAAC, 2015), we selected 280 most heavily traveled routes with each carrying at least 300,000 passengers in 2014. These top 280 accounted for about two thirds of the total traffic volume. The 11 large carriers measured by annual passenger traffic carried were considered in our study. They are Air China, China Eastern, China Southern, Hainan Airlines, Shanghai Airlines, Shenzhen Airlines, Xiamen Airlines, Sichuan Airlines, Shandong Airlines, Spring Airlines, and Juneyao Airlines. We treat each route direction as a market. For example, Beijing-Shanghai and Shanghai-Beijing are treated as two separate markets. There are 558 markets and 3,226 products in the economy-class sample and 558 markets and 2,896 products in the business-class sample.

Following Berry and Jia (2010) and Wang et al. (2017), in the demand function the following characteristics are included in the vector X_{jmt} in model (1): the number of quarterly flights, the average size of aircraft, the route flying distance, a direct flight dummy, a dummy denoting the presence of HSR, the HSR travel speed, the average number of HSR stations at two endpoint cities, and airline dummies.

4.2. Instrument variables

Both price and airline flight frequency can be endogenous as they could be correlated with unobservable product characteristics ξ in equation (9). To deal with the endogeneity issue, following previous studies (Berry and Jia, 2010; Luo, 2015; Wang et al., 2017), the following instruments variables (IVs) z_t are used for the demand moments with strong exogeneity assumption $\mathrm{E}\left(\xi_t \middle| z_t\right) = 0$:

- the number of rivalry products available in the market;
- the percentage of rivalry products that offer direct flights in the market;
- the number of carriers in the market;
- the hub status of each airline in the market;
- the 25th percentile and 75th percentile of fitted fares in a market[3].

The characteristics of the rival airlines in the same market are included as IVs because they are excluded in the passenger utility function derived from consuming one particular product (u_{ijt} is the utility to consume product j , which does not directly depend on the product characteristics of other products). These variables are nevertheless correlated with the price of the consumed product via the markups in the first-order conditions of airline competition (Berry, 1994). These IVs are not as the traditional ones from the cost side, which shift the price due to higher operating cost, while do not directly affect demand. That is, with imperfect competition, demand-side instruments can be variables that affect markups as well as variables that affect marginal costs (BLP, 1995). Specifically, the number of rivalry products and carriers available in the market, and the percentage of rivalry products that offer direct flights in the market reflect the competition intensity in the market, which are from the supply side. They are likely to affect the markup (i.e., the airfare) as it indicates the airline competition, while this variable may also indicate the level of marginal costs as direct flights are more expensive to operate. In addition, the airline's hub status can affect its operating cost, as the airline's unit operating cost can be lower at its own hub due to economies of density and scope. As we have controlled for the

[3] The fitted fares are obtained from quantile regressions of fares on the following exogenous variables: distance, tour, the arithmetic average population at two endpoint airports, the number of carriers, carrier's share of cities at both the origin and the destination airport; airline dummies and year and quarter dummies.

impact of airline's network size in the utility function, such hub status is purely a factor for the airline cost. Last, as documented by Borenstein and Rose (1994, 2007), there was a wide fare dispersion across passengers traveling on the same route. The 25th and the 75th fitted fare quantiles are nonlinear functions of the exogenous route characteristics and can contain the information about the average airfare of the market, thus can be used as IVs.

Airline flight frequency may raise endogeneity concerns since it can also be correlated with the unobservable product characteristics ξ_{jmt}. Flight frequency can also be affected by the increase in air travel utility and demand (airlines increase flight frequency to accommodate higher air travel demand) (Berry and Jia, 2010; Fu et al., 2015a). To address the endogeneity of the flight frequency, we first regress the flight frequency on the characteristics of the end cities, and then using the fitted flight frequency as the IV for the endogenous flight frequency variable (Fu et al., 2015a). The exogenous variables used to fit the flight frequency include endpoint city population, income, number of airport runways, and the existence of HSR competition or not.[4] The descriptive statistics of the key variables used in our study for economy- and business-class passengers are summarized in Table 1.

[4] We do not directly use the IV approach for the endogenous flight frequency variable. This is to avoid the overidentification concern. The direct use of multiple IVs for flight frequency would introduce too many moment conditions in estimations. Instead, the use of the fitted value of flight frequency as IV only introduces one moment condition, which is sufficient to identify the coefficient of the endogenous flight frequency variable, while avoiding estimation bias created by using redundant moment conditions.

Table 1 Descriptive Statistics for Economy-class and Business-class Passengers

	Economy-class					Business-class				
Variables	**Mean**	**Std. Dev.**	**Min**	**Max**	**Unit**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Unit**
Fare	117.07	41.81	14	381	USD	232.10	122.66	50	1,169	USD
No. of Flights	195.87	190.23	30	2,218	Quarterly	191.24	187.78	30	2,218	Quarterly
Avg. Aircraft Size	31,262.08	37,217.01	100	613,329	Quarterly	32,142.67	37,849.78	100	613,329	Quarterly
Distance	1,146.17	514.48	254	3,278	Kilometer	1,136.08	507.18	254	3,278	Kilometer
GDP Per Capita	26.99	16.85	2.26	135.11	RMB 1,000	27.03	16.92	2.26	135.11	RMB 1,000
Population	8.45	4.29	0.77	24.17	Million	8.41	4.30	0.77	24.17	Million
No. of Carriers	4.07	1.39	1	9	Unit	3.87	1.26	1	8	Unit
HHI	4,033	1,631	1,524	10,000	Unit	4,713	1,773	1,293	10,000	Unit

5. Estimations Results and Discussions

5.1. Demand estimates

Tables 2 and 3 show demand estimates for economy- and business-class passengers, respectively. Columns 2, 3 and 4 of the two tables present results for three sub-samples based on airline route distances (<500 km; 500-1,000 km; >1,000 km). As distance increases, the magnitudes of the impact of airfare drops and the importance of flight frequency increases for both economy- and business-class passengers. Distance is positively associated with air demand except in short-distance samples (column 2). This is intuitive since as distance grows, fewer substitutable transport modes are available for passengers. Both economy- and business-class passengers prefer non-stop flights over one-stop flights, especially for long-distance trips. However, the magnitude for business passengers is bigger than that for leisure passengers.

Table 2 IV Demand Function Estimation for Economy-class Passengers

	(1) 2SLS with HSR	(2) 2SLS Distance (<500)	(3) 2SLS Distance (500-1000)	(4) 2SLS Distance (>1000)
Fare	-0.0241***	-0.0382***	-0.0185***	-0.0217***
	(0.0007)	(0.0034)	(0.0008)	(0.0009)
No. of Flights	0.0040***	0.0024***	0.0039***	0.0049***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)
$\tilde{\lambda}$	0.7753***	0.8769***	0.8116***	0.7177***
	(0.0082)	(0.0200)	(0.0119)	(0.0144)
Distance	0.0015***	-0.0005	0.0008***	0.0016***
	(0.0001)	(0.0007)	(0.0001)	(0.0001)
Avg. Aircraft Size	0.0032***	0.0024***	0.0025***	0.0039***
	(0.0001)	(0.0006)	(0.0002)	(0.0002)
Connection	-1.2126***	-0.0266	-0.3756**	-1.6898***
	(0.0730)	(0.4376)	(0.1607)	(0.1152)
3U	-0.2759***	0.1993	-0.4824***	-0.1983*
	(0.0584)	(0.2296)	(0.0834)	(0.1061)
9C	-0.7957***	-1.0581*	-0.3025***	-0.6727***
	(0.0808)	(0.5892)	(0.1123)	(0.1358)
CA	-0.0833	-0.1182	-0.1420*	-0.1333
	(0.0534)	(0.2103)	(0.0739)	(0.0980)
CZ	-0.0840*	-0.0461	-0.1853***	-0.1176
	(0.0498)	(0.1983)	(0.0694)	(0.0909)
FM	0.1155*	0.1145	0.1772**	0.0346
	(0.0654)	(0.2659)	(0.0899)	(0.1204)

HO	0.0640	-0.7801*	0.1375	0.1777
	(0.0759)	(0.4334)	(0.1013)	(0.1379)
HU	0.0344	-0.1108	-0.0211	0.1128
	(0.0515)	(0.2119)	(0.0714)	(0.0940)
MF	-0.1255**	-0.4017	-0.3759***	0.1827
	(0.0591)	(0.2482)	(0.0768)	(0.1133)
MU	-0.2176***	-0.1442	-0.2457***	-0.1926**
	(0.0498)	(0.2085)	(0.0702)	(0.0901)
SC	-0.1932***	-0.4925**	-0.1807**	-0.1285
	(0.0623)	(0.2441)	(0.0815)	(0.1199)
Constant	-5.8004***	-2.6438***	-5.6410***	-6.6815***
	(0.0687)	(0.4440)	(0.1277)	(0.1330)
Own price elasticity	-0.75	-4.72	-1.34	-0.27
Value of flight frequency (per week)	$1.99	$0.75	$2.53	$2.71
Value of direct flight	$50.32	-	$20.30	$77.87
N	76664	6049	26512	44103

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

Table 3 IV Demand Function Estimation for Business-class Passengers

	(1) 2SLS with HSR	(2) 2SLS Distance (<500)	(3) 2SLS Distance (500-1000)	(4) 2SLS Distance (>1000)
Fare	-0.0100***	-0.0133***	-0.0109***	-0.0093***
	(0.0001)	(0.0009)	(0.0003)	(0.0002)
No. of Flights	0.0059***	0.0062***	0.0056***	0.0056***
	(0.0002)	(0.0007)	(0.0003)	(0.0002)
$\tilde{\lambda}$	0.5589***	0.5651***	0.6499***	0.4997***
	(0.0050)	(0.0211)	(0.0078)	(0.0063)
Distance	0.0013***	-0.0001	0.0013***	0.0017***
	(0.0000)	(0.0008)	(0.0002)	(0.0000)
Avg. Aircraft Size	0.0071***	0.0097***	0.0066***	0.0071***
	(0.0002)	(0.0009)	(0.0003)	(0.0003)
Connection	-2.2251***	0.0000	-0.9042*	-2.7111***
	(0.1541)	(.)	(0.5217)	(0.1408)
3U	-0.1866***	0.3053	-0.5007***	-0.1786***
	(0.0579)	(0.2603)	(0.1061)	(0.0532)
CA	0.2624***	-0.2003	0.1600	0.3619***
	(0.0561)	(0.2524)	(0.0976)	(0.0539)
CZ	0.0606	-0.6328***	-0.2350**	0.2755***
	(0.0529)	(0.2435)	(0.0922)	(0.0501)
FM	0.3407***	0.3640	0.3095***	0.3335***
	(0.0669)	(0.2978)	(0.1148)	(0.0647)
HO	0.3986***	-0.3657	0.2365*	0.5986***
	(0.0758)	(0.4846)	(0.1299)	(0.0704)
HU	0.2997***	-0.2046	-0.0084	0.5281***

	(0.0517)	(0.2384)	(0.0916)	(0.0483)
MF	-0.1720***	-0.5411*	-0.5731***	0.0790
	(0.0599)	(0.2854)	(0.0988)	(0.0601)
MU	-0.0464	-0.4172	-0.1571*	0.0545
	(0.0540)	(0.2890)	(0.0944)	(0.0507)
SC	-0.3161***	-0.9359***	-0.5520***	-0.1670***
	(0.0628)	(0.2767)	(0.1039)	(0.0636)
Constant	-10.7017***	-9.2173***	-10.2013***	-11.6280***
	(0.0588)	(0.4407)	(0.1464)	(0.0734)
Own price elasticity	-0.21	-1.69	-0.26	-0.07
Value of flight frequency (per week)	\$7.08	\$5.59	\$6.17	\$7.23
Value of direct flight	\$222.51	-	\$82.95	\$291.52
N	72704	5833	25459	41412

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

With the utility function estimates, we can calculate the passenger market-level price elasticity. This is done by simulating the airline market share change by assuming all the airline products have 1% price increase (Berry and Jia, 2010; Yan and Winston, 2014). The average price elasticity for economy-class passengers is -0.75 while for business-class passengers is -0.21. When differentiating route distance, we found that air passengers are far more price-sensitive in short-distance markets than in long-distance markets, which is expectable since many other transport modes exist in short-distance markets. Earlier studies such as Zhang et al. (2013) and Wang et al. (2018a) estimated that the airline price elasticity was around -1.0 for economy-class air passengers in the Chinese market. Unlike this paper, their study periods did not cover the growing penetration of HSR expansion in the period after 2014. It is reasonable to see a smaller value of the price elasticity as those passengers very sensitive to prices would have been switched to HSR. We also complement earlier studies with the business-class passengers' price elasticity estimates. Despite the much lower average personal income, the airline price elasticities (Tables 2 and 3) in China are comparable to those in the US (Berry and Jia, 2010; Yan and Winston, 2014).

Using the compensating variation between airfare and other airline product variables, we calculate air passengers' values of flight frequency and direct flight. Specifically, the value of weekly flight frequency is 7.08 USD (or daily flight frequency as 49.56 USD) for business-class passengers, approximately three times bigger than that of economy-class passengers. Our estimated flight frequency value for the economy-class passenger is comparable to Yan and Winston (2014) for the San Francisco Bay Area market. Our estimate for the business-class passenger is quite similar to Berry and Jia (2010) on the entire US market. Our estimated value of direct flights is 291.52 USD for Chinese business-class passengers, which is also around three times larger than that of economy-class passengers. This is quite similar to the estimates in Berry and Jia (2010) and Yan and Winston (2014). As distance increases, passengers place more value on flight frequency and direct flights. All these results demonstrate very similar air travel patterns and preferences between Chinese and American passengers.

5.2. Air passenger welfare analysis

In this part, we analyze air passengers' welfare changes after the entry of HSR. HSR affects airline passengers' utility in two ways, namely, by affecting the airfare and flight frequency. To capture the impact of HSR on airfare and air frequency, a DID analysis is conducted. The treatment group consists of the routes with HSR entry, while the control group refers to those routes without HSR entry. The selected sample routes are the same as the ones used in airline demand estimation. Moreover, to capture the possible lag effect of HSR on the airfare and air frequency, an interaction term of HSR dummy and the number of quarters after HSR entry is added. The models are set as follows:

$$\begin{aligned}\ln fare_{mt} = {} & \theta_0 + \theta_1 HSR_{mt} + \theta_2 HSR_{mt} \times EntryQuarters_{mt} + \theta_3 \ln POP_{mt} \\ & + \theta_4 \ln GDP_{per_{mt}} + \theta_5 \ln routeHHI_{mt} + \theta_6 \ln airportHHI_{mt} \\ & + \delta_m + \sigma_t + \varepsilon_{mt}\end{aligned} \tag{12}$$

$$\begin{aligned}\ln flight_{mt} = {} & \gamma_0 + \gamma_1 HSR_{mt} + \gamma_2 HSR_{mt} \times EntryQuarters_{mt} + \gamma_3 \ln POP_{mt} \\ & + \gamma_4 \ln GDP_{per_{mt}} + \gamma_5 \ln routeHHI_{mt} + \gamma_6 \ln airportHHI_{mt} + \omega_m \\ & + \vartheta_t + \varphi_{mt}\end{aligned} \tag{13}$$

where

- $\ln fare_{mt}$ is the logarithm value of market-level quarterly airfare.
- $\ln flight_{mt}$ is the logarithm value of market-level quarterly flight frequency.
- HSR_{mt} is a dummy variable which equals 1 if the HSR enters in market *m* at time *t*.
- $EntryQuarters_{mt}$ is the number of quarters after the HSR enters the market.
- $\ln POP_{mt}$ is the logarithm value of the arithmetic mean of city populations at the two endpoints of each route.
- $\mathrm{lnGDP}_{\mathrm{per}_{\mathrm{mt}}}$ is the logarithm of the arithmetic mean of city GDP per capita at the two endpoints of each route.

- $\ln routeHHI_{mt}$ is the logarithmic form measuring market concentration level on a route. It is computed based on quarterly passenger volume carried by each airline on a route.
- $\ln airportHHI_{mt}$ is the logarithmic form measuring airline concentration level at the endpoint airports. This airport HHI is calculated using each airline's traffic share at the airport.
- δ_m, and ω_m are market-level fixed effects.
- σ_t, and ϑ_t are quarterly time fixed effects.
- ε_{mt} and φ_{mt} are error terms.

The results of DID analysis are shown in Tables 4 and 5. The results of the economy class (Table 4) show that in all the markets the negative impact of HSR on airfares faded away with time. In the short-distance market, the airfares did not change significantly immediately after the entry of HSR. However, this came at the cost of a heavy cut in flight frequency by 44.6% on average. In fact, some airlines even canceled their services completely on the short-distance routes in response to HSR competition. This is sensible in that airline and HSR services are more competitive on the short-distance routes. When HSR just entered the market, cutting the capacity was a natural and simple response to maintain prices. However, over time, airlines would become adapted to the presence of HSR and could work out other strategies including finding a new niche market, and charging relatively lower prices to retain and attract passengers. In contrast, in the medium- and long-distance markets (columns 3 and 4 of Table 4), the entry of HSR would cause only a slight drop in flight frequency. This is because airlines hold a relatively fixed fleet size and have little flexibility to change supply network-wise (Wang et al., 2014). Once the flights were cut substantially on those short-distance routes, airlines were unable to do the same on the other routes. With a relatively unchanged supply and a decrease in airline demand, a slightly lower airfare was seen on the medium- and long-distance routes. Meanwhile, airlines could also possess stronger market power on the medium- and long-distance routes due to the less substitutability of HSR. To compensate for the profit loss on the short-distance routes, airlines may have to do everything possible to stabilize or even increase the prices including engaging in tacit collusion (Ma et al., 2019b, 2020).

It is interesting to see from Table 5 that HSR competition led to an even larger percentage drop in frequency for flights with business-class passengers than for economy-class passengers.[5] As HSR is cheaper and more punctual than air transport in China, many employers

[5] Many flights offer both business and economy classes, while some only economy class. The flights with business class passengers should also provide services to economy-class passengers. The samples for these two markets are selected independently of each other in this study.

have made the new travel policy that HSR is the first choice for their employees' business travel, especially for short- and medium-distance travels. This may have had led to a larger drop in demand and thus frequency for flights with business-class passengers. On the short-distance routes, the drop was 54% on average immediately after the entry of HSR. However, the prices for business-class passengers remained relatively stable. On the other hand, in the medium-to-long-distance markets, airlines continuously cut the frequency of the flights with business class, which resulted in a slight rise in business-class fares (about 4%), demonstrating the nature of inelastic demand of this type of travelers.

Table 4 DID analysis for economy-class passengers

Fare equation estimation for economy-class passengers					**Flight frequency estimation for economy-class passengers**				
	(1)	**(2)**	**(3)**	**(4)**		**(1)**	**(2)**	**(3)**	**(4)**
	All markets	**Distance**	**Distance**	**Distance**		**All markets**	**Distance**	**Distance**	**Distance**
		<500	**500-1000**	**>1000**			**<500**	**500-1000**	**>1000**
HSR	-0.0410***	0.0221	-0.0439***	-0.0383***	HSR	-0.0822***	-0.4461***	-0.0778***	-0.0195
HSR*EntryQuarters	0.0115***	-0.0087***	0.0150***	0.0101***	HSR*EntryQuarters	-0.0084***	0.0215***	-0.0105***	-0.0102***
lnPOP	0.0426***	0.0188	0.0233	0.0800***	lnPOP	0.2771***	-0.0823	0.0712*	0.5302***
lnGDP_per	0.0223**	0.0889**	0.0067	-0.0155	lnGDP_per	0.2120***	-0.0676	0.0771**	0.4224***
lnrouteHHI	0.1583***	0.1664***	0.1770***	0.1289***	lnrouteHHI	-0.7621***	-0.8555***	-0.7309***	-0.6989***
lnairportHHI	0.0470***	-0.0326	0.1132***	0.0153	lnairportHHI	0.013	0.7596***	-0.0135	-0.2622***
Constant	2.4101***	2.8519***	1.7293***	2.6607***	Constant	8.8942***	8.1980***	11.2975***	7.3577***
N	21609	1977	7438	12194	*N*	21609	1977	7438	12194
R^2	0.275	0.332	0.282	0.292	R^2	0.457	0.242	0.446	0.554
Year dummies	√	√	√	√	Year dummies	√	√	√	√
Quarter dummies	√	√	√	√	Quarter dummies	√	√	√	√
Market fixed effects	√	√	√	√	Market fixed effects	√	√	√	√

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

Table 5 DID analysis for business-class passengers

Fare equation estimation for business-class passengers					Flight frequency estimation for business-class passengers				
	(1)	**(2)**	**(3)**	**(4)**		**(1)**	**(2)**	**(3)**	**(4)**
	All markets	**Distance <500**	**Distance 500-1000**	**Distance >1000**		**All markets**	**Distance <500**	**Distance 500-1000**	**Distance >1000**
HSR	-0.0346***	0.0258	-0.0900***	0.0111	HSR	-0.1330***	-0.5428***	-0.0977***	-0.0877***
HSR*EntryQuarters	0.0174***	-0.006	0.0229***	0.0137***	HSR*EntryQuarters	-0.0073***	0.0311***	-0.0114***	-0.0076***
lnPOP	0.0757***	-0.105	0.065	0.1099***	lnPOP	0.2455***	-0.1968***	0.0579	0.5115***
lnGDP_per	0.1242***	-0.3072***	0.0175	0.2722***	lnGDP_per	0.2829***	-0.1384	0.0858**	0.5743***
lnrouteHHI	0.4003***	0.3665***	0.3985***	0.4003***	lnrouteHHI	-0.5295***	-0.6034***	-0.5066***	-0.4871***
lnairportHHI	0.2597***	0.4683***	0.2317***	0.2612***	lnairportHHI	-0.0836***	0.5625***	-0.0401	-0.3538***
Constant	-1.3788***	-1.3622	-1.2750*	-1.5792***	Constant	7.9629***	8.7477***	9.6833***	6.4111***
N	21534	1965	7390	12179	*N*	21534	1965	7390	12179
R^2	0.454	0.461	0.478	0.445	R^2	0.403	0.225	0.381	0.506
Year dummies	√	√	√	√	Year dummies	√	√	√	√
Quarter dummies	√	√	√	√	Quarter dummies	√	√	√	√
Market fixed effects	√	√	√	√	Market fixed effects	√	√	√	√

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

To better illustrate our econometric estimation results, we pick up a couple of airline routes for a closer look. Fig. 2 shows the airfare and air frequency trends for some representative markets. The left panel of Fig. 2 shows an example in the short distance market, namely Shanghai-Wenzhou (SHA-WNZ). Immediately after the launch of SHA-WNZ HSR, airlines reacted by dramatically cutting the capacity, which helped stabilize airfare in the short run. However, two to three years later, the frequency started to go up and airfares dropped. The right panel in Fig. 2 shows a case of Beijing-Ningbo (PEK-NGB), which is a long-distance market. In the short term, the percentage drop in air frequency was less than that of the airfare. However, in the long run, the air frequency presented a decreasing trend but airfares kept increasing. Besides the two representative routes, we also observe quite similar frequency and airfare change patterns on the short-distance and medium-to-long-distance routes, respectively.

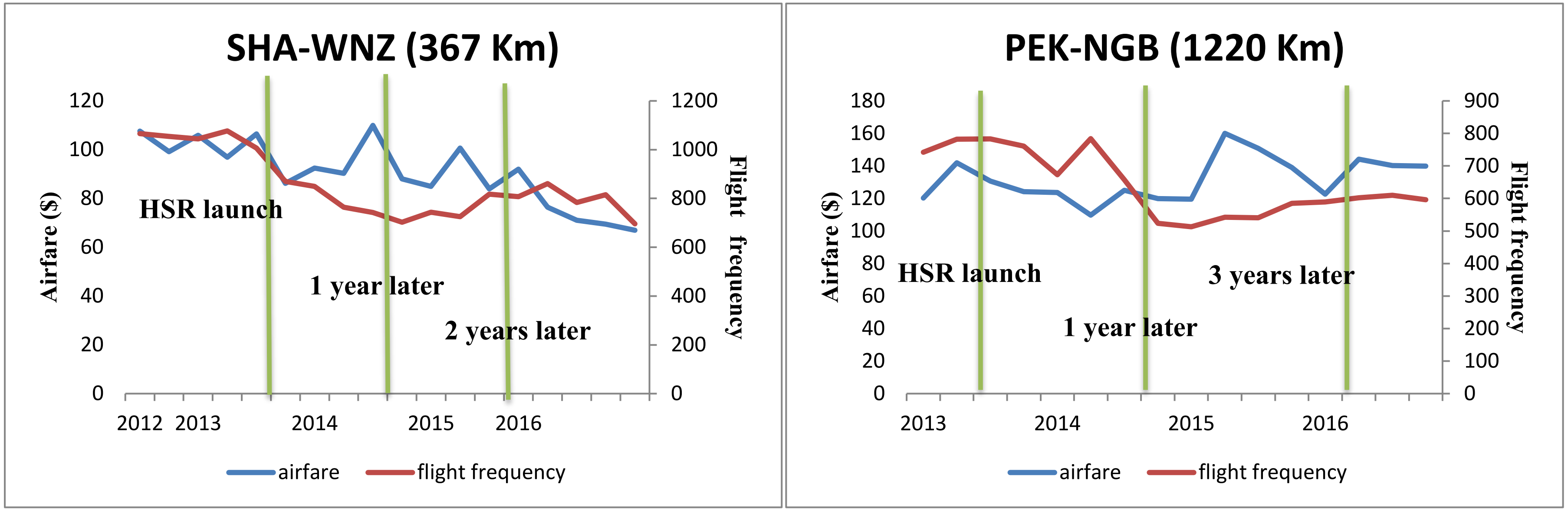

Fig. 2 Representative markets to demonstrate DID estimation results

Now, with our DID estimated changes in airfare and flight frequency and the estimated passenger utility function, we can calculate the passenger welfare changes for each airline route due to HSR entry. This is done for both economy- and business-class passengers on different routes. To have a general idea, we first plot the distribution of the average economy-class passenger welfare change in the short-, medium-, and long-run (Fig. 3-5). In each figure, we also distinguish among route distances. Fig. 6-8 plot the corresponding results for the business-class passengers.

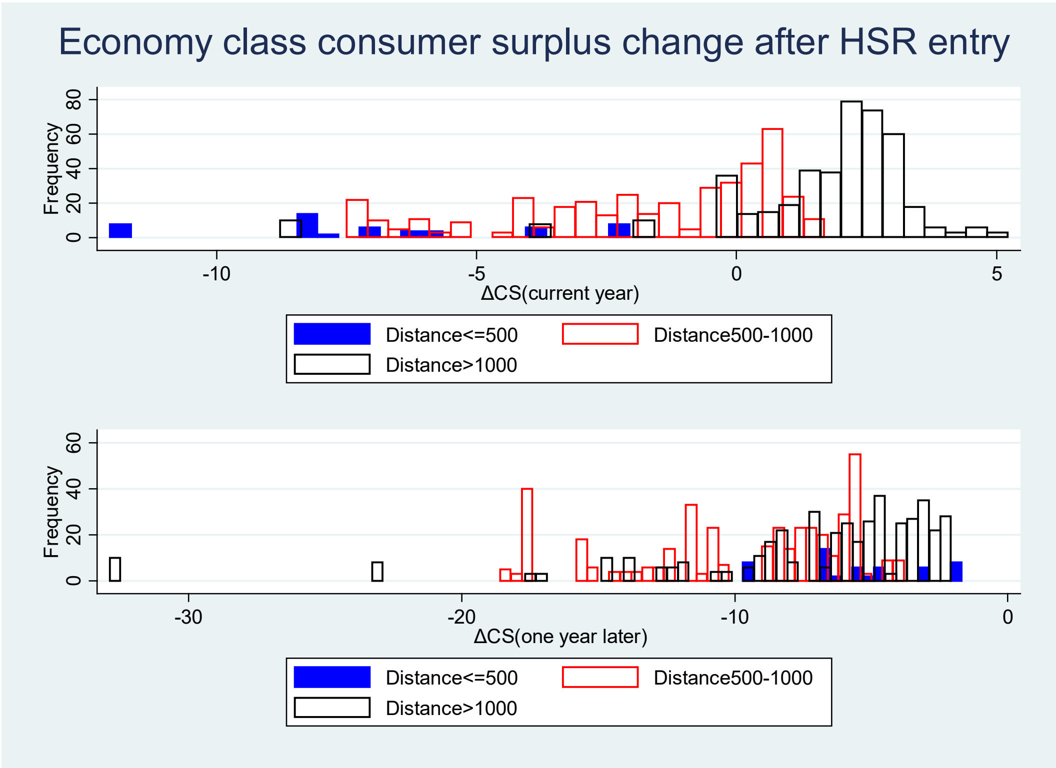

Fig. 3 Changes in economy-class consumer surplus (immediately and one year after the HSR entry)

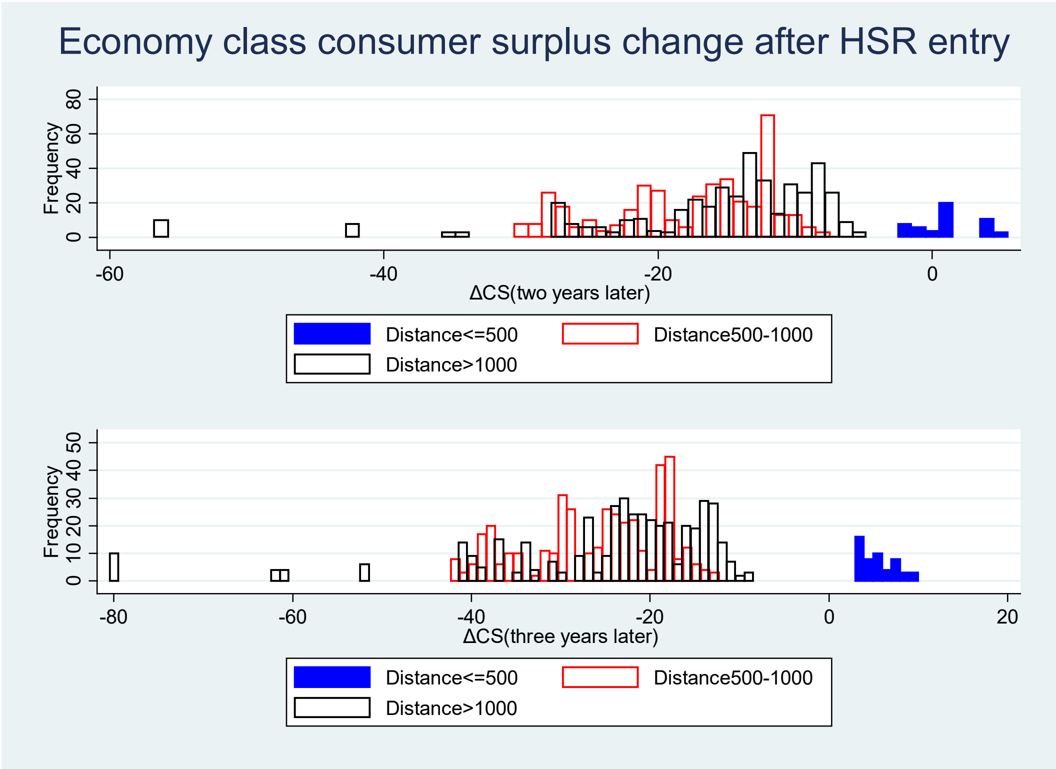

Fig. 4 Changes in economy-class consumer surplus (two and three years after the HSR entry)

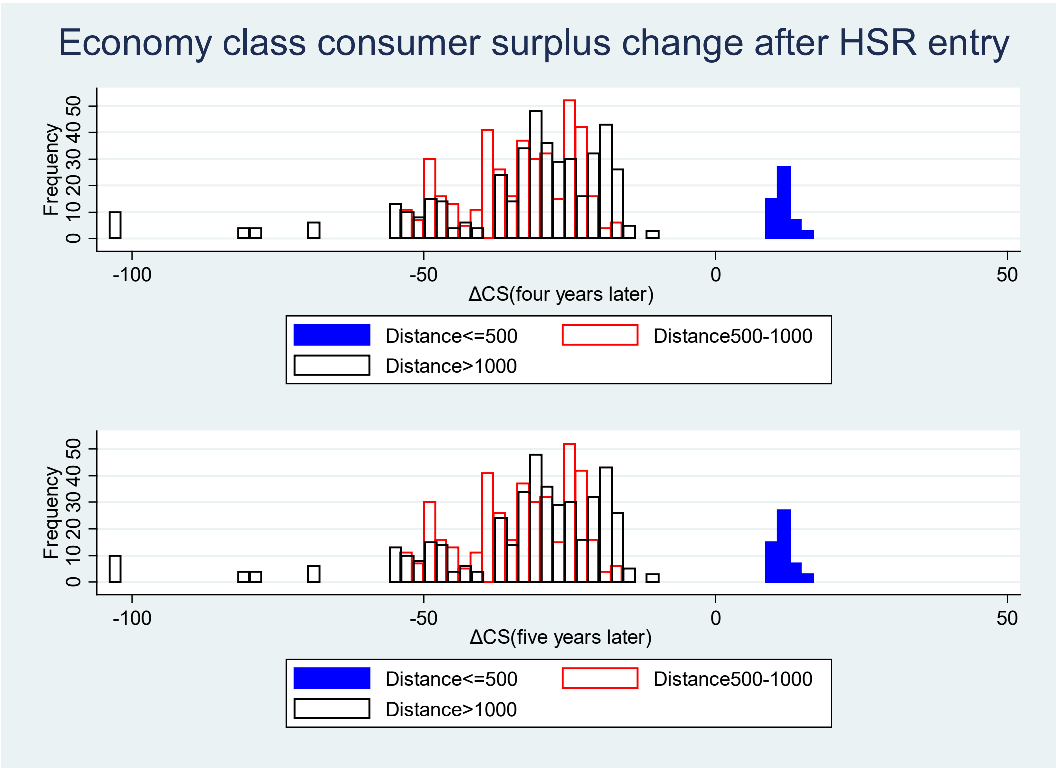

Fig. 5 Changes in economy-class consumer surplus (four and five years after the HSR entry)

Fig. 3 shows the welfare change per economy-class passenger in the short run after HSR entered the market. We observe that the economy-class passengers in the short-distance markets would be worse off immediately or one-year after the HSR entry. This is consistent with the DID analysis that the flight frequency dropped sharply but airfares remained almost the same shortly after the entry of HSR. In other words, passengers did not enjoy an airfare reduction due to HSR competition, but had to suffer a lower flight frequency. On the other hand, in the medium- and long-distance markets, the economy-class passengers could be better off in the short run after the HSR entry. This is because the flight frequency in these markets would only drop slightly but with a much lower airfare. However, over time (see Fig. 4 and 5), the economy-class passengers' welfare on the short-haul routes gradually improved while the medium- and long-distance passengers were worse off. This is because in the long term, in the short-distance markets, air frequency tended to go up and airfare would drop. In contrast, in the long-distance markets, the air frequency decreased and airfares increased, resulting in a reduction in consumer welfare. Similar trends are found for business-class passengers in Fig. 6-8.

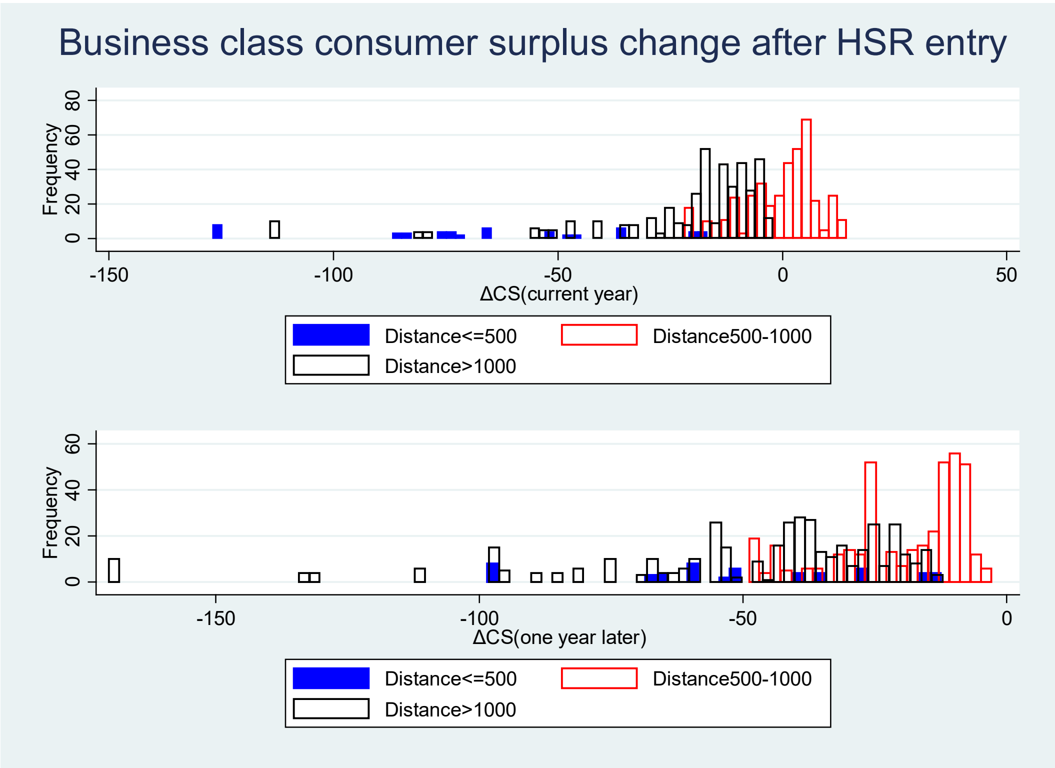

Fig. 6 Changes in business-class consumer surplus (immediately and one year after the HSR entry)

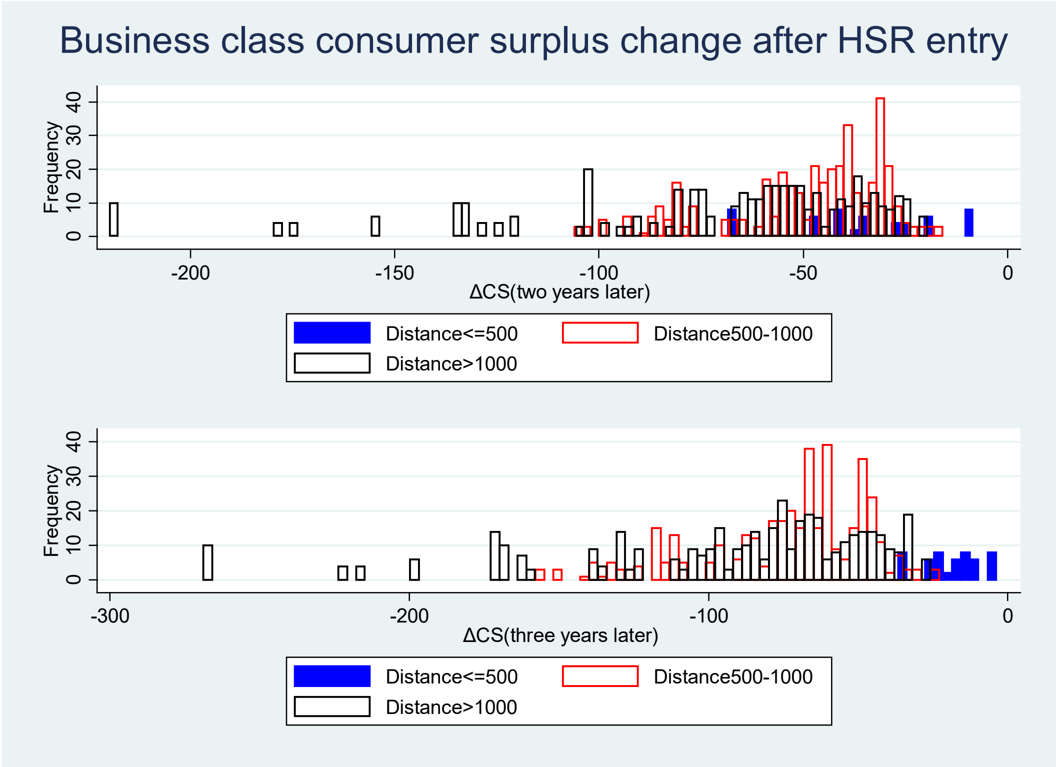

Fig. 7 Changes in business -lass consumer surplus (two and three years after the HSR entry)

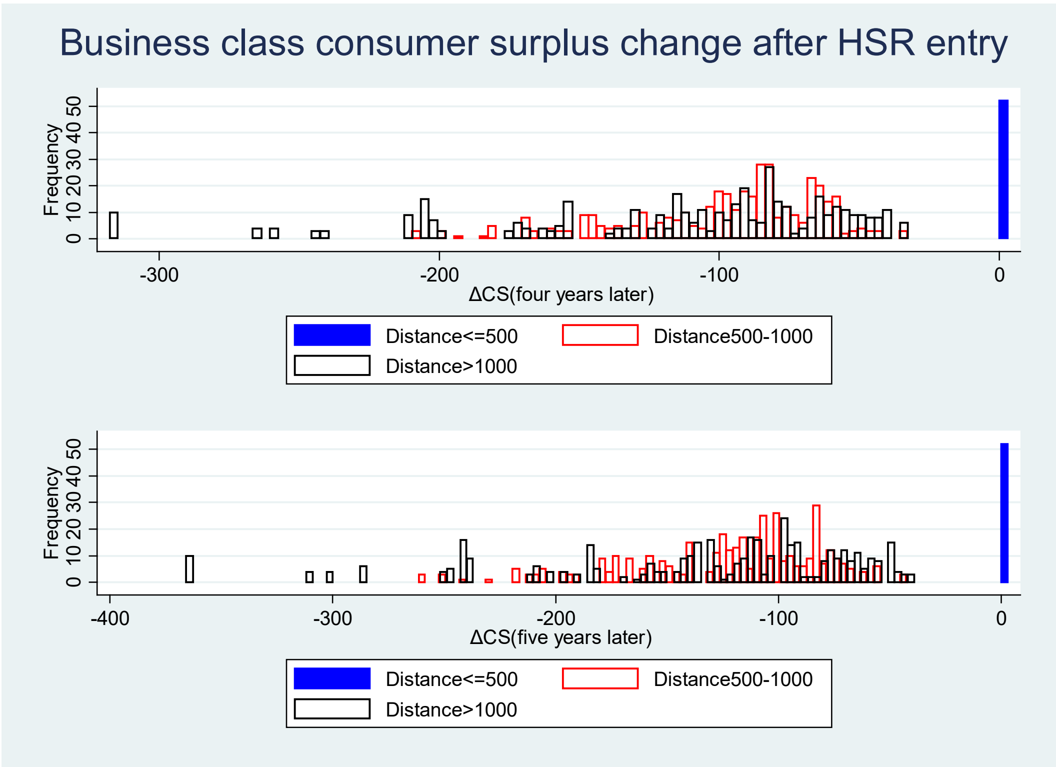

Fig. 8 Changes in business-class consumer surplus (four and five years after the HSR entry)

To better quantify and compare welfare changes for economy- and business-class passengers, Tables 6 and 7 calculate the per-passenger welfare change after the HSR entry for each type of passengers. Table 6 shows that in the first two years after the entry of HSR, the economy-class flight frequency dropped sharply due to a dramatic demand reduction. Reduced demand coupled with supply reduction resulted in a decrease in consumer surplus by US$5.5-6.9 per economy-class passenger. From the third year to the sixth year after the entry of HSR, the flight frequency was gradually added back to short-distance routes while the prices went down by 5.65%-16.13%. Therefore, air passengers' welfare started to improve by an amount of about US$1-14.68 per passenger. On the medium- and long-distance routes, in the first year after the entry of HSR, the flight frequency was only marginally affected by HSR, and the prices dropped by a small amount. Air passengers thus were slightly better off in this period. However, from the second year to the sixth year after the HSR entered, airlines continued to reduce flight frequency in the medium- and long-distance markets. As a result, the market price increased and air passengers were worse off. For example, six years after HSR entered the long-haul routes, there was a reduction in consumer welfare by US$42.2 per economy-class passenger.

As shown in Table 7, business-class passengers experienced much larger welfare loss than economy-class passengers. On the short-distance routes, both the flight frequency and air traffic dropped sharply in the first few years after the HSR entry. As business-class passengers tend to place a higher value on flight frequency (Zhang, 2012), the frequency drop led to a greater reduction in passenger welfare. Nevertheless, as time went on, airlines added back the flights on these routes, alleviating the welfare loss for the business-class passengers. On the other hand, in the medium- and long-distance markets, airlines continuously cut flight frequency. Given that business-class passengers place a higher value on flight frequency, they suffered a greater loss in consumer surplus than economy-class passengers. For instance, six years after the HSR entered the medium- and long-distance markets, business-class airline passengers could lose US$133.41-135.16 in consumer surplus per person. This is approximately three times larger than the loss by economy-class passengers.

Table 6 Airfare, flight frequency, and consumer surplus changes per economy-class airline passenger due to the HSR entry

Distance (Km)		**1 year after HSR entry**	**2 years after HSR entry**	**3 years after HSR entry**	**4 years after HSR entry**	**5 years after HSR entry**	**6 years after HSR entry**
<500	△Airfare	No significant change	No significant change	-5.65%	-9.14%	-12.64%	-16.13%
	△Flight frequency	-42.50%	-33.86%	-25.25%	-16.65%	No significant change	No significant change
	△Airline CS	-$5.50	-$6.90	+$1.00	+$5.57	+$11.51	+$14.68
500-1000	△Airfare	-2.89%	+3.12%	+9.13%	+15.14%	+21.15%	+27.15%
	△Flight frequency	-8.78%	-12.98%	-17.17%	-21.37%	-25.56%	-29.76%
	△Airline CS	-$1.74	-$9.79	-$17.8	-$25.8	-$33.77	-$41.71
>1000	△Airfare	-2.82%	+1.23%	+5.28%	+9.34%	+13.39%	+17.44%
	△Flight frequency	-2.96%	-7.03%	-11.10%	-15.16%	-19.23%	-23.30%
	△Airline CS	+$1.50	-$7.32	-$16.11	-$24.85	-$33.55	-$42.20

Table 7 Airfare, flight frequency, and consumer surplus changes per business-class airline passenger due to the HSR entry

Distance (Km)		**1 year after HSR entry**	**2 years after HSR entry**	**3 years after HSR entry**	**4 years after HSR entry**	**5 years after HSR entry**	**6 years after HSR entry**
<500	△Airfare	No significant change	No significant change	No significant change	No significant change	No significant change	No significant change
	△Flight frequency	-51.57%	-38.71%	-26.25%	-13.79%	No significant change	No significant change
	△Airline CS	-$51.00	-$65.70	-$35.46	-$19.08	No significant change	No significant change
500-1000	△Airfare	-6.71%	No significant change	+11.60%	+20.75%	+29.90%	+39.06%
	△Flight frequency	-10.91%	-15.48%	-20.04%	-24.60%	-29.17%	-33.74%
	△Airline CS	-$0.17	-$19.86	-$49.37	-$73.59	-$113.92	-$135.16
>1000	△Airfare	No significant change	+7.98%	+13.47%	+18.96%	+24.46%	+29.95%
	△Flight frequency	-9.53%	-12.56%	-15.59%	-18.63%	-21.66%	-24.69%
	△Airline CS	-$20.75	-$49.10	-$70.94	-$92.50	-$112.59	-$133.41

6. Conclusion

The paper for the first time looks into airline consumer welfare in China in the era of HSR. The first part of this paper uses a reduced-form BLP model to estimate demand and utility functions of airline business- and economy-class passengers. The second part of this paper applies counterfactual analysis to calculate air passengers' welfare change in each market after the HSR entry, considering HSR's lag impact on airfares and air frequency. We find that business- and economy-class passengers have different preferences when making choices among products. Business-class passengers prefer higher frequency and direct flights more than economy-class passengers. The price elasticity, value of weekly flight frequency and value of direct flight for each type of passengers are calculated. We also computed the air passenger surplus changes after the HSR entry, which exhibit different patterns in the short and long run, as well as in the markets with different distances.

In general, it has been found that both economy- and business-class passengers have inelastic demand and all the passengers appreciate higher flight frequency. Immediately after the HSR entry, air passengers in the short-distance markets were worse off, driven by a dramatic cut in frequency. Over time, their welfare in these markets could improve when flights were added back and airfares dropped. In contrast, air passengers in the medium- and long-distance markets could be better off immediately after the entry of HSR due to lower airfares offered. However, a reduction in welfare was observed over time, as airlines gradually reduced flight frequency. The welfare changes to economy- and business-class passengers exhibit similar patterns but differ in magnitudes.

The findings of this research have significant policy implications to airline management, aviation regulators and anti-trust authorities. First, despite the heavy penetration of HSR in China, there is still a great potential for China to develop its airline market, evidenced by the Chinese air passengers' low price elasticity of demand. Individual carriers can develop their brands to make the demand for their individual services even more inelastic. For China's full-service airlines (FSAs), developing an LCC subsidiary as their competition arm against HSR can be a consideration in response to the penetration of HSR given that the LCC sector has not been well developed in China, compared to the European, North American and Southeast Asian markets (Fu et al., 2015b; Wang et al., 2017; Wu et al, 2020). In fact, there is an opportunity for both transport modes to survive and prosper considering China's huge population and rapidly growing economy. Second, this study shows that when faced with HSR competition, Chinese airlines tend to restrict output, particularly on the medium- and long-distance routes in the long run where HSR is less substitutable. This reduces consumer welfare. It is not known if Chinese airlines have resorted to collusive agreements to manage prices and market shares, but the anti-trust authorities need to be vigilant and the air-HSR competition deserves close monitoring (Zhang, 2011; Zhang and Round, 2011; Zhang, 2015).

Finally, it should be cautioned that our welfare calculation is restricted to the passengers who stick to the air travel and would not choose or switch to HSR. Theoretically, for those switching to HSR services, their welfare must have increased post the HSR entry. Therefore, when evaluating the overall welfare effect of air-HSR competition for all inter-city travelers, it is likely that there would be an improvement in consumer welfare. However, our study is still meaningful in view of the fast-growing air transport market in China, where a large proportion of travelers mainly choose air travel. Future studies can consider modeling and estimating passengers' choices between transport modes and the associated welfare changes, which are not addressed in this study.

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