City-pair air connection under high-speed railway development: Simulation of air travel demand affected by the new Chinese High-Speed Rail lines opening in 2030

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Abstract

High-speed rail (HSR) is increasingly challenging air transport operations in China due to its competitive edge in frequency, better accessibility from city centers (in particular when considering door-to-door travels), and overall convenience for short to medium distance travel. This increasing demand changes will become even more extensive in the next decades with laid out high speed rail development plans. By the end of 2020 the railway network of China had expanded to include around 40.000 km of HSR lines (equal to 2.2 times the extent of 2013) and the milestone for 2030 until 2050 is to reach more than 70.000 km of HSR lines. Accordingly, airlines are under increasing pressure to adapt their networks in order to be efficient and profitable. In this study, we develop a demand forecasting model with the goal to analyze the effect of increased high-speed railway penetration on air markets passengers flows from 2012 to 2019 and predict what will be the impact for the domestic aviation sector for the next two decades with the new railway lines planned to be opened by 2030. We propose and compare different econometric specifications, highlighting the advantages of using a declination using a semi-logarithmic OLS to predict the total city-pair market demand, reaching an accuracy of around 80% when validating the model on an unseen set of test data. Specifically, our analysis evaluates the air demand shift towards rail in city pairs that will benefit from new HSR lines opening in 2030. Our results show that for the majority of cities connected below 550 km, the air transport will likely be replaced by the HSR connection by 2050, while for cities connected between 550 and 2000 km of distance the air demand will substantially decrease but without completely disappearing. Moreover, the results clearly show the relationship between distance and the introduction of HSR: the closer the origin and destination cities, the sooner the majority of passengers demand shift from air transport to HSR. Our research contributes to the discourse on sustainable transportation planning, highlighting the potential implications for policymakers, urban planners, and transportation industry stakeholders.

Keywords: Demand forecasting; HSR entry; socio-economic future scenarios; passengers' utility shift.

1. Introduction

Over recent decades, a consistent increase in the number of air passengers can be observed across major markets in the world. The main factors contributing to this growth include rising incomes,

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a trend towards globalization, increased affordability of air travel, and an overall improved connectivity (Hofer et al., 2018; Hanson et al., 2022; Ozmec-Ban and Babić, 2023). This growth trend has been interrupted temporarily through the COVID-19 outbreak, with a significant disruption of air transportation and times of volatile demands (Sun et al., 2021b, 2022). Nevertheless, the overall growth trend is projected to continue, with forecasts anticipating a steady rise in air travel demand, particularly in relationship to emerging markets, such as the Asia-Pacific region. According to IATA (International Air Transport Association)[1], in China the airline industry has been experiencing a strong recovery. Domestic air travel surged by 272% in November 2023 compared to the previous year, driven by the lifting of travel restrictions. IATA forecasts that international demand in the Asia-Pacific region, including China, will reach 92% of 2019 levels in 2024, fully recovering to 101% by 2025. Specifically, China's domestic air demand is expected to exceed pre-pandemic levels, reaching 111% by 2024 and 118% by 2025. China however is also strongly committed to the future use of high-speed railway technology in order to prepare its domestic transportation for sustainable future (Sun et al., 2017; Li et al., 2024). China's high-speed railway network is already the world's longest network at about 40.000 km, essentially constructed within less than one and a half decades (Ren et al., 2023). According to plans from the Chinese government, the high-speed rail network will reach more than 70.000 km within the next two decades[2]. The impact of this development on airlines is wide-reaching, forcing Chinese' domestic airlines to reduce airfare and cancel many (earlier highly-profitable) regional flights (Liu et al., 2019). The major advantages of high-speed rail are its competitive edge in accessibility from city centers (Sun et al., 2021a) and frequencies (Zhang et al., 2019b), and overall convenience for short to medium distance travel.

The interaction between high-speed rail (HSR) and air transport can be understood through the lens of intermodal competition models, which are rooted in discrete choice theory and transportation economics (Bergantino and Madio, 2020; Ma et al., 2025). In these models, travelers are assumed to choose between available transport modes by minimizing their generalized travel costs, a composite measure encompassing monetary costs (fares), in-vehicle travel time, access and egress times, service frequency, reliability, comfort, and other convenience factors (Song et al., 2018; Huan et al., 2024; Wang and Xu, 2024). Intermodal competition arises because improvements in one mode (e.g., faster, more frequent, or more accessible HSR services) alter the relative attractiveness of competing modes, thereby shifting market shares. Empirical studies show that HSR tends to dominate short- to medium-distance city pairs where travel times are competitive with air transport and access to urban centers is convenient (Nerja and Sánchez, 2025). Conceptually, this framework also captures network effects and induced demand: as HSR networks expand, connectivity improves, effectively lowering generalized costs for additional trips and reinforcing mode substitution (Nurhidayat et al., 2023).

Although the expansion of HSR in China was initially aimed at upgrading conventional rail and enhancing inter-city mobility rather than directly targeting air transport, overlaps in medium-distance markets (roughly 500–1000 km) have nonetheless created significant competition between HSR and airlines. Numerous studies have analyzed the impacts and policy implications of air-HSR competition, covering both short-term and long-term effects on airline profits (Jiang and Zhang, 2016; Tsunoda, 2018; Chen et al., 2023), parallel airline services (Gonzales-Savignat, 2004; Román et al., 2007; Chen et al., 2020), and route-level demand (Park and Ha, 2006; Wang et al., 2018a; Liu et al., 2019; Zhang et al., 2019b). Studies also examine passenger behavior, such as willingness-to-

[1]Press Release No. 2 in date 10 January 2024.
[2]Information available at the following: https://www.chinadaily.com.cn/a/202403/12/WS65ef9ab2a31082fc043bc032.html

pay and modal choice, in the context of air-HSR competition. Research suggests that factors like HSR frequency and travel time significantly influence airline performance (Behrens and Pels, 2012; Zhang et al., 2019b), while HSR can attract passengers from both air transport and car users on long-haul trips (Martín and Nombela, 2007). In China, HSR has notably decreased traffic demand for airlines, especially on short-haul routes, and has positively impacted tourism development (Zhang et al., 2017; Chen et al., 2023). The introduction of HSR has had a substantial negative effect on air demand for short-haul routes (less than 850 km) where air-HSR substitutability is high (Wang et al., 2018a). Additionally, recent studies like (Zhu et al., 2021) have explored how HSR impacts air-HSR competition under conditions of high flight delays, particularly in the Beijing-Shanghai corridor.

In response to the introduction of HSR, airlines have implemented various strategies to mitigate its impact, including adjusting flight frequencies, modifying pricing strategies, and enhancing service quality. Studies have explored how airlines adapt by reallocating capacity and revising network configurations to stay competitive (Fu et al., 2010; Bilotkach and Lakew, 2014). Research also examines how airlines adjust airfare and traffic scheduling when HSR is introduced (Gu and Wan, 2022), as well as the effect of HSR on airline pricing strategies and competition between full-service carriers and low-cost carriers on high-demand routes (Su et al., 2019, 2020).

Nevertheless, while a variety of econometric models in the literature are capable of producing forecasts, relatively few studies have explicitly applied them to assess the potential effects of planned HSR lines that have not yet been implemented. Existing work has largely concentrated on evaluating the realized impacts of current HSR on air routes and market dynamics, whereas ex-ante investigations are more often based on survey data or accessibility indicators. Only a limited number of studies address the potential role of HSR projects that are still under construction. For example, new HSR development may influence ground accessibility, offering insights into the broader reshaping of transportation networks (Wang et al., 2018b). Similarly, the expansion of the Chinese HSR network over the past decade has been analyzed through a connectivity index to evaluate the degree of city integration within the system (Zhou et al., 2018a,b). By contrast, research on the relationship between HSR and air transport demand has been predominantly retrospective. For instance, the impact of HSR on air demand up to 2017 has been assessed (Strauss et al., 2021), reductions in air demand through 2019 have been analyzed (Chen et al., 2025), and the adaptation of the Chinese city-pair air network to HSR expansion between 2009 and 2019 has been investigated (Yang et al., 2023). These studies provide important evidence of realized impacts, but they do not extend to discuss the potential effects of future HSR projects. Besides the meaningful intuition of the studies, there is no prominent research direction regarding the influence that the current HSR infrastructure development can have for air city-pair markets demand in the long-term future. Given that infrastructure projects require substantial investment and have long lifespans, it is crucial to forecast how ongoing HSR development may influence air city-pair demand in the coming decades. Such forecasts they offer valuable forward-looking insights that can support strategic planning and policy evaluation.

In this paper, forecasting models provide valuable insights into how future HSR developments might reshape air travel demand and network configurations in established air domestic city-pair markets. This study represents a pioneering effort in forecasting the timing, extent, and specific corridors where a significant portion of passenger demand may be expected to shift from air transport to HSR. By addressing this gap, stakeholders can better anticipate the strategic responses of aviation sector, thereby enriching the understanding of the evolving dynamics between air and rail transportation modes.

In our study, we focus on the Chinese context and develop a city-pair market demand forecasting model leveraging an historical dataset spanning from 2003 to 2019, integrating different data sources. We use data from 2012 to 2019 for leveraging variables able to capture not only the air market supply development and the socio economic characteristics, but also the presence and the competing influence of HSR development that has been integrated through different features[3]. As core of our research, we conduct a case study investigation on 2030 China railway expansion plan with 20 years forecasts[4]. By applying the forecasting models to HSR expansion plan, the study provides valuable insights into the long-term projections of HSR development on air travel demand, offering a forward-looking perspective that is crucial for strategic planning. For this purpose, we employ socio-economic data projections (Chen et al., 2020; Wang et al., 2022; **?**). By employing future socio-economics projections, we ensure that the demand predictions account also for anticipated changes in population, economic growth, enhancing reliability and robustness of the forecasts. The findings of this research will be highly relevant for policymakers, transportation planners, and airline managers. The ability to predict the impact of HSR expansion on air travel demand can inform infrastructure investment decisions, strategic planning for airlines, and policy formulation aimed at optimizing the transportation network.

The rest of the paper is organized as follow. Section 2 provides a comprehensive literature review about air demand forecasting and HSR competition. Section 3 explains the data and features used, the methodological framework as long as the variables elaborated for the demand prediction purpose. Section 4 shows the results, discuss the accuracy of the proposed models and the influence of different types of variables. Section 5 discusses the development of new HSR lines 2030, shows a first empirical explorative analysis of the network impact and finally apply the forecasting model to the new set of city pairs, presenting which cities will be mostly affected by the shift air-HSR. Finally, Section 6 concludes the study.

2. Literature review

In this section, we provide a literature review discussion on the relation between air transport and HSR.

Table 1 provides an overview of key contributions in the literature on air–HSR competition, outlining their geographical focus, period of analysis, level of aggregation, and the type of demand predicted. Beyond summarizing these elements, the table also highlights the most common perspectives adopted in existing studies while illustrating the heterogeneity in approaches and findings across different research contexts. Several studies focus exclusively on the Chinese market, reflecting the significant interest in understanding the dynamics between HSR and air transport domestically. For example, analyses centered on China have examined how HSR impacts the air transport sector within the country (Wang et al., 2015; Zhang et al., 2019b, 2024). This focus is particularly important given China's rapid railway network expansion and its profound implications for air travel. Very few studies attempt to predict near-future air demand trends while considering future railway network expansions (Wang et al., 2015; Kroes and Savelberg, 2019; Ma et al., 2024). In particular, there is also a focus on hinterland regions in China and the overlapping markets of air transport and

[3]Data regarding the opening of HSR lines have been collected within the time period 2003-2020.

[4]since the most updated literature provide robust socio-economic projections until 2050. Please refer to Section 3 for a comprehensive discussion regarding data sources.

Table 1. Summary of literature for air-HSR competition.

Literature	Geography		Time period		Aggregation		Demand predicted	
	China	Others	Ex-post	Ex-ante	Market level	Carrier level	HSR	Air
(Givoni and Dobruszkes, 2013)		✓	✓		✓		✓	
(Albalate et al., 2015)		✓	✓		✓			✓
(Wang et al., 2015)	✓			✓	✓			✓
(Li and Sheng, 2016)	✓		✓		✓			✓
(Wang et al., 2018a)	✓		✓			✓		✓
(Kroes and Savelberg, 2019)		✓		✓	✓			✓
(Li et al., 2019)	✓		✓		✓		✓	
(Zhang et al., 2019b)	✓				✓			✓
(Bergantino and Madio, 2020)		✓	✓			✓		✓
(Gu and Wan, 2020)	✓		✓		✓			✓
(Wang et al., 2020b)		✓	✓		✓		✓	
(Cai et al., 2021)	✓		✓			✓	✓	
(Strauss et al., 2021)	✓		✓		✓			✓
(Yu et al., 2021)	✓		✓		✓			✓
(Wu and Han, 2022)	✓		✓			✓	✓	
(Nurhidayat et al., 2023)		✓	✓			✓	✓	
(Lee et al., 2024)	✓		✓			✓	✓	
(Ma et al., 2024)	✓			✓	✓			✓
(Zhang et al., 2024)	✓		✓		✓			✓
Our study	✓			✓	✓			✓

Geography = Geographical context of the study.
Time period = Historical analysis (ex-post) or future lines (ex-ante).
Aggregation = Whether carrier-level analysis is used.
Demand predicted = Type of demand predicted (air or HSR).

HSR (Wang et al., 2015). Due to the lack of long-term socio-economic projection data, the study predicts only the short-term impact of HSR, while acknowledging that the long-term effects remain unclear. The most notable finding is that HSR demonstrates the most significant competitive advantage on medium-distance routes. The majority of studies conduct their analysis at the market level, examining overall trends in air travel demand without delving into the competitive dynamics of individual airlines (Li and Sheng, 2016; Li et al., 2019; Gu and Wan, 2020; Strauss et al., 2021; Yu et al., 2021). Some studies explicitly focus on predicting HSR demand (Givoni and Dobruszkes, 2013; Wu and Han, 2022), also by examining the accessibility of HSR stations and its impact on HSR–air competition in the Chinese domestic context (Wu and Han, 2022). Others concentrate on air demand prediction from a carrier-level perspective (Wang et al., 2018a; Nurhidayat et al., 2023; Lee et al., 2024). These studies highlight the trade-offs and competitive interactions between the two modes of transportation, providing insights into how HSR expansion can influence air travel patterns.

However, from the previous studies, it emerges that the competitive worldwide pressure did not always result in the overall reduction in total air travel demand, which in some contexts increased thanks to operators reorganizing their routes (Clewlow et al., 2014; Sun et al., 2024) and to forms of air-HSR integration, with improvements in transport connectivity—such as new HSR lines or airline routes—also promoting broader interactions and activity between cities (Ma and Huang, 2024). In particular in the European context, a common finding across the literature is that the presence of HSR stations in airports might compensate airlines for the effects of competition with HSR (Albalate et al., 2015; Dobruszkes, 2025; Kampp et al., 2025), while improvements in HSR travel speeds have also been shown to reduce short-haul air passenger volumes, particularly on domestic routes, highlighting the nuanced effects of HSR expansion on airline traffic (Oesingmann and Ennen, 2025). Moreover, environmental and policy-oriented analyses suggest that restricting short-haul flights in favor of HSR can further shift passengers toward rail, reinforcing modal substitution and supporting sustainability objectives (de Bortoli and Féraille, 2024). A subsequent literature has further explored forms of air-HSR integration from a theoretical (see e.g., Jiang et al. (2017); Jiang and Zhang (2014); Xia and Zhang (2016)) and empirical perspective (e.g., Givoni and Banister (2007); Li and Sheng (2016), among others). On short and medium haul distances, as for the Chinese domestic market, changes in operators' business strategies when facing the introduction of HSR have twofold dimensions: the supply-side and the demand-side. Many empirical studies addressed the former. For instance, some contributions have shown that airlines reacted to the introduction of HSR with changes in the number of flights (Jiménez and Betancor, 2012; Dobruszkes et al., 2014; Chen, 2017) and seats (Dobruszkes et al., 2014; Albalate et al., 2015; Wan et al., 2016; Chen, 2017). Yet, the demand dimension is also relevant. When HSR is introduced, transport demand becomes more elastic as passengers have more options to exploit (Zhang et al., 2013, 2017). Previous papers have shown that the introduction of HSR services can lead to a significant change in demand (De Rus and Nash, 2007; Clewlow et al., 2014; Chen, 2017; Nurhidayat et al., 2023). Partly, this is dependent on the greater attractiveness of HSR due mainly to the reduced impact of access and egress time (Wang et al., 2018a; Bergantino and Madio, 2020; Xu et al., 2023). In addition, competition from HSR can induce airlines to improve service quality, such as reducing departure delays and operational inefficiencies, which may mitigate some of the potential loss of air demand and influence passenger choices (Fang et al., 2025). More recent studies extend these approaches by explicitly linking HSR–air competition to broader socio-economic outcomes, such as urban economic growth, through competition network analysis and spatial econometric modeling (Su et al., 2025).

The methodologies employed in the literature on air demand forecasting under HSR competition encompass a wide range of quantitative and comparative techniques, each tailored to specific research questions. For instance, comparative analysis and case studies have been used to investigate competitive dynamics in the European context, with a focus on pricing, frequency, and passenger volumes (Albalate et al., 2015). In contrast, regression analysis and time-series forecasting have been applied to historical data to capture demand trends in integrated air–HSR services along the Beijing–Guangzhou corridor (Li and Sheng, 2016). Similarly, econometric approaches, including fixed-effects and random-effects regressions, have been employed (Zhang et al., 2019b). Other studies rely on gravity-model formulations (Strauss et al., 2021; Yu et al., 2021), while panel regression (Li et al., 2019) and difference-in-differences (DID) frameworks (Wang et al., 2018a) have also been implemented. Moreover, discrete choice and modal split models have been developed (Kroes and Savelberg, 2019), whereas econometric modeling integrated with simulation techniques—combining price competition models, travel time difference analysis, and catchment area expansion scenarios—has been used to assess the effects of HSR entry on air traffic (Gu and Wan, 2020).

In conclusion, most of the reviewed literature assesses the impacts of HSR retrospectively, focusing on realized effects observed in historical data. While forecasting models are likewise estimated from historical evidence, their application to planned HSR expansions allows us to translate past relationships into forward-looking scenarios. This provides projections of how future air travel markets may evolve under upcoming HSR developments. Such forecasts are particularly valuable for policy makers and industry stakeholders, as infrastructure projects require large-scale investment and have long lifespans. By linking established empirical evidence with future expansion plans, forecasting studies can inform strategic planning and decision-making regarding the interplay between HSR and aviation.

The novelty of our study lies in providing demand projections upon the opening of Chinese new HSR lines in 2030 and highlight which connections are more likely to show a huge air-HSR demand shift, providing evidence of the pivotal role of the distance between cities. More specifically, we integrate the demand forecasting model under HSR presence and the plan of Chinese HSR expansion (along with robust socio economic projections for the next decades), offering insights into future developments under different demographic development frameworks. Three major contributions of our study are summarized as follows: (i) We empirically investigate and demonstrate the competition aspect between domestic civil aviation and HSR in China, giving evidence of the scenarios in which HSR takes more advantage over air transport; (ii) Taking into account the air-rail competition, we estimate the share of air demand that has been displaced by HSR due to its competitive advantage and in which time horizion (e.g., in the next 5 years, 10 years, 20 years); (iii) Given the new set of HSR market connections for the next decades, we evaluate the competitive travel time advantage and the future demand shift; moreover, under several civil aviation and socio economic scenarios we highlight the set of cities where domestic aviation sector will likely be under most pressure.

3. Data and Methods

[5] This section details the data sources and forecasting methodology employed in our analysis. Section 3.1, provides an overview of the datasets utilized, including their origins, types, and the relevant information collected. It outlines the rationale behind selecting these sources and how they contribute to the study. Section 3.2, describes the variables and models specifications applied to analyze the data. It covers the methodological approach for forecasting air passengers demand under HSR presence, detailing the econometric models used and the criteria for evaluating model performance.

3.1. Data sources

This study employs a wide range of data sources to thoroughly analyze the impact of HSR on air domestic demand in China. To ensure a comprehensive examination of the evolving dynamics between air transport and HSR, we integrate data spanning from 2003 to 2050.

[5]To ensure the robustness and generalizability of the model, the dataset was restricted to the pre-pandemic period (2012-2019). Data from 2020 to 2023 were intentionally excluded to avoid distortions arising from the COVID-19 pandemic, which caused unprecedented and short-term fluctuations in air and rail travel behavior. Including these years could bias model coefficients by capturing temporary disruptions rather than long-run structural relationships. By focusing on a relatively long and heterogeneous pre-pandemic period, the analysis captures stable trends in the interaction between air transport and HSR, providing a reliable foundation for forecasting demand patterns beyond 2030 under the assumption that long-term drivers, such as economic growth, infrastructure expansion, and modal competition will continue to evolve along historical trajectories.

Our primary data on flight schedules, including flight frequency, seat availability, carrier information, and travel times, was obtained from the OAG Schedule Analyser for the years 2012 to 2019. This dataset is complemented by passenger numbers and distance data from the OAG Traffic Analyser for the same period. These data sources provide a detailed view of air travel patterns and are instrumental in understanding market dynamics within metropolitan areas (city), which are grouped according to OAG's classification system. HSR entry data, detailing the introduction of HSR lines from 2003 to 2020, was manually collected from government and railway official websites. This dataset helps track the temporal expansion of the HSR network and its potential effects on transportation dynamics. Looking forward, we incorporate data on HSR backbone lines planned for 2030 as outlined in the Medium and Long-Term Railway Network Plan (2016), providing projections of HSR network expansion. Additionally, socio-economic projections segmented by province from 2025 to 2050 (Chen et al., 2020; Wang and Sun, 2022; Wang et al., 2022) are used to forecast long-term transportation demand by considering future demographic trends. Travel time data for public transportation and car travel, sourced from OpenStreetMap (OSM), offers city-based values that highlight accessibility and convenience for itineraries starting and ending in city centers. This data is essential for evaluating the competitive travel time advantage of HSR compared to air transport, particularly in new HSR connections. Population and GDP data from the China Statistical YearBook, covering 2009 to 2019, provide insights into demographic trends and economic conditions across various cities. This information is crucial for understanding the broader socio-economic context influencing transportation demand.

Our dataset comprises approximately 500.000 observations, each detailing an origin city, destination city, carrier operating, and monthly frequency, covering about 5.000 unique origin-destination markets. Our analysis includes city-pairs with a minimum of 20 flights per month and routes that remained in continuous operation until 2019. Moreover, all city-pairs include HSR-related information, considering whether they are connected via a direct train (referred to as 'non-stop') or with a single transfer (referred to as 'one-stop'). These comprehensive data sources (see Table 2 for a detailed overview) form the foundation of our demand forecasting model. They enable us to capture the intricate interactions between HSR and air transport, and to predict the potential impacts on aviation market efficiency and profitability as the HSR network continues to expand.

3.2. Forecasting methodology

This subsection is divided into two key sections. Section 3.2.1 details the process of preparing and transforming raw data into meaningful variables that are used in our forecasting models. It explains how features are derived from the data sources, including the creation of new variables and their utility into the model. Section 3.2.2 describes in details the forecasting techniques and models employed to analyze the air travel demand. It outlines the selection of econometric models, the approach to model training and validation, and the criteria for evaluating model performance.

3.2.1. Features Engineering[6]

In our demand forecasting model, we consider a range of variables to capture the multifaceted interactions between air transport and HSR. These variables are critical for understanding the

[6] With this term we refer to the process of transforming raw data into meaningful variables (features), such as using seat capacity data to construct a Herfindahl–Hirschman Index (HHI) or socioeconomic indicators to calculate a compound annual growth rate (CAGR).

Table 2. Data Sources used in the study.

Data Sources	Variables	Usage	Time period
OAG Schedule Analyser	Air scheduling and supply data	Modeling air demand	2012–2019
OAG Traffic Analyser	Air demand data	Modeling air demand	2012–2019
Open Street Map	Public transportation and car travel time	Case study on new HSR lines	-
China Statistical Yearbook	GDP per capita and population data	Modeling air demand	2009–2019
Chinese Railways Official Websites	HSR lines opening and city connected	Modeling air demand	2003–2020
Medium and Long Term Railway Network Plan	HSR lines to be opened in 2030	Case study on new HSR lines	2016–2030
(Chen et al., 2020; Wang et al., 2022; Wang and Sun, 2022)	GDP and population projections	Case study on new HSR lines	2025–2050

determinants of air passenger demand and predicting how it evolves with the increasing penetration of HSR (see Table 3 for overview descriptive analytics).

Table 3. Descriptive Analytics of variables used in the study.

Variable	**Mean**	**St Dev**	**Min**	**Median**	**Max**
Distance (km)	1386	839	300	1892	2373
Passengers	59,701	30,444	50	65,167	345,264
Pop ('0000)	48,767	17,244	1,749.7	55,945	211,912
GDP per capita ($)	12,899	5,235	12,618	13,115	17,213
Frequency	55	72	5	88	1152
Seats	8,659	11,788	210	5,053	191,268
Travel time ratio	0.9	1	0.2	0.8	1.2
Feeding HSR	45	57	25	73	112
Age HSR (years)	7	3	1	5	12

Population (*Pop ('0000)*) and GDP (*GDP per capita ($)*) are node-based values.
Distance, Passengers, Frequency, Seats, Travel time ratio, Feeding HSR, and Age HSR are link-based variables at monthly level.
Thousand separator is a comma "," and decimal separator is a point ".".

Our dependent variable is the number of passengers, it reflects the current demand for air travel on a given route. It is denoted by D^t_{od}, where we index origin and destination market by o and d, time periods by t. Analyzing this variable also with a one-year lag allows us to observe demand trends and persistence over time.

Distance is a fundamental variable that directly influences travel mode choice (defined as distance in kilometer in our model). Longer distances generally favor air travel due to its speed advantage, whereas shorter distances may be more competitively served by HSR. To capture non-linear effects, we also consider the squared form of distance.

Frequency refers to the number of flights scheduled in a market pair. Higher frequency increases convenience and flexibility for passengers, enhancing the attractiveness of air travel. Within the empirical model we analyze frequency with a one-year lag and we also account for the change (delta) between time periods to understand how past frequency adjustments impact current demand. As we have also data at airline level, frequency of competitors on the same route has been considered, measuring the supply level offered by all competing airlines. This variable, along with its one-year lag, helps in understanding the competitive landscape and how it influences a carrier's market share and passenger demand.

The Herfindahl-Hirschman Index (HHI) is used to measure market concentration. It is calculated using the number of seats offered by each carrier relative to the total market seats. Higher HHI values indicate less competition, which can affect pricing and service quality, thereby influencing passenger demand[7]. For reducing endogeneity issues with the dependent variable, we consider it with 1 year lag.

Socio economic information are given by population[8] and gross domestic product variables. These indicators are used to capture the underlying drivers of air travel demand and are essential for forecasting future demand by incorporating the anticipated socio-economic and demographic developments of the regions included in the analysis. More in particular, population data helps in understanding the potential market size for both air and rail travel. Larger populations typically correlate with higher travel demand. GDP per capita serves as an indicator of economic activity and the ability of the population to afford travel. Higher GDP per capita usually indicates higher demand for both air and rail travel services[9]. The Compound Annual Growth Rate (CAGR) measures the annual growth rate of a variable over time, providing insights into long-term trends in air travel demand or supply metrics. In our study, it has been applied to both population and GDP per capita.

To model the impact of HSR on the aviation market, we use three key variables. First, we assess the ratio of HSR travel time to air travel time, incorporating additional waiting times[10]: 90 minutes for air travel and 60 minutes for HSR. In Section 5.1 we have reported the rationale of adding waiting times during a travel time itinerary computation, as well as the proposal of four different scenarios that have been tested and evaluated, (following Koppelman et al. (2008); Moyano et al. (2018); Wang et al. (2020a)). After the sensitivity analyses has been conducted, Figure 9 and 10 show that once the waiting times have been introduced, there's no significant difference in the total travel time itinerary evaluation; therefore, we have adopted the combination of waiting times with the lowest time difference between air and HSR. By selecting the scenario with the smallest waiting time difference between HSR and air travel, we have positioned ourselves in the most stringent scenario. This approach assumes a lower likelihood of HSR being more convenient only thanks to reduced waiting times, thereby setting a higher benchmark for HSR's competitiveness. This decision ensures that any observed advantages of HSR in our analysis are robust, as they occur under conditions that are least favorable to HSR's perceived convenience relative to air travel. We also add 30 minutes to the HSR time if the itinerary involves a single stop, acknowledging that Chinese HSR networks are often designed such that one-stop routes can be faster and more efficient than direct flights offering smooth connection experience. This is crucial

[7] It assumes values ranging from 0 to 1 where 0 is the perfect competition and 1 is a monopolistic market.

[8] Please note that the population values in Table 3 should be read, for instance, as 487,67*10.000 = 4.876.700.

[9] Both population and GDP variables within the empirical model have been engineered by taking the product of values at origin and destination cities.

[10] Waiting times includes the time required to travel between city center and airports/HSR stations, as well as time spent at stations or airports before departure, security checks, boarding, and other pre-travel procedures.

because China's HSR network is strategically structured to optimize travel efficiency, with many one-stop itineraries potentially outperforming non-stop air travel due to the network's extensive coverage, central station locations, and streamlined boarding processes. Second, we include an HSR feeding variable, which measures the connectivity of an area by summing the number of cities linked by HSR to both the origin and destination. This variable captures the extent of connectivity and the importance of an area as a hub within the HSR network, reflecting its potential to support and facilitate additional connections. Third, age of HSR variable is represented in the logarithmic form of the number of months since the HSR line opened. If between the origin and destination cities there's no direct HSR connection and the itinerary has to be computed by 1-stop travel connection, then the age HSR for that itinerary is assumed to be the age of the youngest leg between the two. This variable captures the maturation effect of HSR services, where newer lines may gradually attract more passengers over time as they become better known and trusted.

Lastly, trend variable elaborated as continuous time index ranging from 1 to 8 is included, representing the study period's years. This variable helps capture underlying time-related effects that could influence demand in a time-series analysis context.

Incorporating these variables into our demand forecasting model allows for a nuanced analysis of the factors influencing air passenger demand in the context of increasing HSR presence.

3.2.2. Modeling

To analyze the impact of HSR on airline network structures and forecast air passenger demand, we adopt an econometrics methodological framework. This framework involves dataset preparation, model formulation, and evaluation using key performance indicators (KPIs). The dataset is split into two subsets for model training and testing, the training set uses data from 2012 to 2017, the test set uses data from 2018 to 2019 for validate the predictive performance[11].

We employ a Ordinary Least Square (OLS) with a semi-logarithmic regression formulation incorporating the HSR competition, the formulation follows the specification (following Birolini et al. (2021)):

$$\ln(Y) = \beta_0 + \beta_j X_j + \beta_i ln(X_i) + \epsilon \tag{1}$$

For the linear terms X_j[12], the coefficients β_j represent the change in $\ln(Y)$ for a one-unit change in X_j, which corresponds to an approximate percentage change in Y[13]. For the logarithmic terms $\ln(X_i)$, the coefficients β_i represent the elasticity of Y with respect to X_i, i.e., the percentage change in Y for a one-percent change in X_i. The semi-logarithmic OLS formulation is particularly beneficial when the relationship between the dependent and independent variables is multiplicative rather than additive. By taking the natural logarithm of the dependent variable, we transform a non-linear relationship into a linear one, thus applying linear regression techniques. Additionally, the

[11]Although OLS regression provides unbiased estimates of coefficients under classical assumptions, splitting the dataset into training and testing subsets allows us to evaluate the model's predictive performance on unseen data, rather than only its fit to the sample used for estimation. By training the model on 2012–2017 data and testing it on out-of-sample 2018–2019 data, we can assess whether the relationships estimated from historical observations generalize to future periods, which is particularly important when the model is intended for forecasting air travel demand under new HSR scenarios. This approach also helps identify potential overfitting and ensures the model's predictive reliability beyond the estimation period.

[12]In this group there are: Lag demand, CAGR pop, CAGR GDP, Lag HHI, Delta freq, Delta freq comp.

[13]In this group there are: Distance, Pop, GDP, Age HSR, Travel time ratio, Trend, Feeding HSR.

semi-logarithmic model is particularly suitable in cases where certain variables are best expressed in logarithmic form, while others are more appropriately kept in their original scale. This is common in economic and transportation studies, where relative changes are often more meaningful than absolute changes[14].

To account for unobserved heterogeneity across city-pairs and exploit the panel structure of the dataset, we complement the semi-log OLS with a Panel Random Effects (RE) specification. The Panel RE model incorporates both within- and between-route variation by introducing route-specific random intercepts, capturing time-invariant characteristics that may affect air travel demand but are not directly observed, such as local infrastructure quality or geographical factors. This approach mitigates potential omitted variable bias and produces more conservative standard errors, leading to robust inference.

To comprehensively analyze the factors and dynamics influencing air passenger demand, we develop multiple model formulations based on different sets of independent variables and aggregation levels. First, we consider formulations M1 and M2, where in the former we consider population and GDP per capita as proxies for the demand as well as the trend variable, in the latter we incorporate lagged demand values to capture the persistence and trend of air passengers over time. For each M1 and M2 formulation, we compare carrier-level vs carrier-aggregated models. The first variant considers observations at the carrier level (allowing for a more granular investigation of market dynamics and yielding specific demand estimates for a given airline, hense being more suitable to inform airline network planning tasks), where each OD pair in a given month can be observed more than once if the market is served by multiple carriers. This allows for a detailed analysis of individual carrier performance and competition. The second variant uses observations aggregated among carriers, providing an overall market-level analysis perspective.

Overall, by testing both the approaches we highlight the importance of selecting appropriate model formulations and specifications to accurately capture demand dynamics. The semi-logarithmic approach, coupled with detailed comparisons between carrier-level and aggregated models, provides an analytical framework for analyzing and forecasting air passenger demand in the context of evolving competition and market conditions.

4. Results

The results from the semi-log formulation, presented in Table 4[15], provide several insights into the factors influencing air passenger demand in the presence of HSR competition. The coefficient estimates exhibit distinct variations between the carrier-specific and aggregated models. These variations underscore the differing dynamics captured by each modeling approach. A comparison with the Panel Random Effects (RE) models further highlights the robustness and interpretation of

[14]When dealing with datasets that include negative values or zeros, directly applying a logarithmic transformation can be problematic, as the natural logarithm is undefined for non-positive numbers. A common workaround is to add a constant (such as +1) to all values before taking the logarithm. However, this approach has significant drawbacks (Webb, 1970; Bagwell, 2005). First, adding a constant can distort the true relationships between variables. The choice of the constant is arbitrary and can significantly affect the results, leading to biased estimates. Second, the resulting coefficients may become difficult to interpret, as the transformation alters the scale and meaning of the original variables. Third, for variables with a substantial number of zeros or negative values, adding a constant can lead to misleading results. It may artificially inflate the values, leading to overestimation or underestimation of the actual effects. Instead, a semi-logarithmic model can be a more robust solution.

[15]Variables denoted in bold characters are those without the application of the log transformation.

these effects. In general, the Panel RE coefficients are slightly smaller in magnitude than the corresponding OLS estimates, reflecting the model's ability to account for unobserved, time-invariant heterogeneity across city-pairs. By explicitly modeling these route-specific effects, the Panel RE specification mitigates potential bias arising from omitted variables that are constant over time but vary across routes. Consequently, standard errors in the Panel RE models are generally more conservative, occasionally reducing the statistical significance of some variables (e.g., GDP, CAGR of population, Age HSR), while the direction and substantive interpretation of the effects remain unchanged. Key determinants—including Distance, Lag demand, Delta frequency, and Feeding HSR—retain strong significance across both approaches, confirming the stability of the primary relationships. Overall, while semi-log OLS provides a transparent baseline for understanding the determinants of air travel demand, the Panel RE specification offers a more robust framework that accounts for unobserved heterogeneity, providing policy-relevant insights into air-HSR competition dynamics.

Distance shows a positive effect on demand in all model specifications. Notably, the effect is significantly larger in the aggregated model for M1 (1.27) compared to the carrier-specific model (0.18). This suggests that on an aggregated level, distance plays a more pronounced role in influencing demand, as expected[16].

When considering M2 specification, the inclusion of lagged demand shows positive coefficients as expected (0.11 for carrier-specific and 0.74 for aggregated), indicating that previous period demand positively impacts current demand, with a stronger effect in the aggregated model. On the other hand, when considering M1 specification socio-economic variables coefficients are taken into account. Population has a positive impact on demand. This aligns with expectations as larger populations generate higher demand for air travel. For population, also the coefficients of the compound annual growth rate are positive across all models, indicating that growing populations drive demand.

When considering M1 specification, the negative coefficient of GDP per capita in the regression model should not be interpreted as evidence that higher income reduces air travel demand. Rather, it reflects the structural characteristics of economically developed metropolitan areas (such as Beijing, Shanghai, and Guangzhou), which are densely served by high-speed rail and other transport alternatives. In these regions, short- and medium-distance air travel is partially substituted by HSR, leading to slower growth in air passenger volumes. Moreover, because population and GDP per capita are correlated, population size captures most of the scale effect of market potential, while GDP per capita captures residual variation related to economic maturity and competitive intensity. Therefore, the negative sign highlights how economic development and HSR accessibility jointly moderate air travel growth, consistent with theoretical expectations of modal substitution and market saturation effects.

We include the Herfindahl–Hirschman Index (HHI) and route frequency with 1 year lag as variables to account for market structure and service intensity, both of which are key determinants of air travel demand. While these variables are potentially endogenous—since low-demand markets naturally support fewer airlines and flights—the use of lagged HHI and frequency mitigates simultaneity bias in the time dimension, ensuring that current demand does not mechanically affect past market structure. The incorporation of these variables improves the model's explanatory power and helps capture realistic cross-sectional and temporal variation in demand. This is particularly important for forecasting future scenarios, such as the introduction of new HSR lines, where ignoring mar-

[16] Note that distance is a market related determinant, hence influencing more the total city-pair market demand than the demand captured by individual airlines

ket concentration or service levels could distort predicted outcomes. Including HHI and frequency aligns with established empirical practice, allowing us to control for market characteristics while focusing on the causal interpretation of other covariates.

The presence of HSR negatively impacts air travel demand across all models specifications, underscoring the competitive pressure HSR presence imposes on air travel. The variables HSR travel time ratio and HSR feeding provide further insights into HSR's role in shaping air travel demand. The positive coefficient for the HSR travel time ratio - which incorporates both non-stop and one-stop itineraries- suggests that shorter HSR travel times are linked to lower air travel demand, reflecting the attractiveness of faster HSR journeys as an alternative mode of transport. The HSR feeding variable, which measures the connectivity of an area by the number of cities linked via HSR, primarily reflects enhanced HSR accessibility. In the context of our study, higher connectivity increases the options for travelers to reach destinations by HSR rather than by air, effectively substituting for air travel. This interpretation is consistent with the negative coefficients observed in our models, ranging from -0.22 to -0.37 in M2 and from -0.31 to -0.28 in M1, highlighting how well-connected HSR hubs can amplify the competitive impact on air travel demand. As demonstrated also by the positive coefficient of age HSR variable in M2 models, this "demand stealing" effect is most acute immediately following the introduction of a new HSR route, as early adopters quickly shift to HSR. When a new HSR route is introduced, it often results in a significant shift in consumer preferences. The immediate availability of a faster, more convenient rail alternative leads to a substantial reduction in air travel demand along the same routes. Over time, the market adjusts, and the impact stabilizes, with remaining air travel demand becoming less sensitive to HSR presence. In M2 specification, a positive coefficient for the variable age HSR indicates that the introduction of new HSR routes has a pronounced and disruptive effect on air travel demand.

Understanding the temporal dynamics of HSR's impact on air travel demand is crucial for demand forecasting and strategic planning. The initial negative impact of new HSR routes highlights the need for airlines to anticipate and adapt to these disruptions quickly. Strategic adjustments in scheduling, pricing, and service offerings can help mitigate the initial loss in demand. Over the longer term, airlines can leverage the stabilized demand to refine their network and service strategies, ensuring they remain competitive in a market where HSR is a significant player.

The key performance indicators (KPI) indicate that the aggregated model with M2 specification is the most accurate one in terms of R2, mean absolute percentage error (MAPE) and mean absolute error (MAE).

Table 4. Results from Semi-Log OLS and Panel Random Effect OLS.

	M1 Semi-Log OLS		**M1 Panel RE OLS**		**M2 Semi-Leg OLS**		**M2 Panel RE OLS**	
	Carrier	Aggregated	Carrier	Aggregated	Carrier	Aggregated	Carrier	Aggregated
Distance	0.18***	1.27***	0.16***	1.15***	0.19***	0.95***	0.18***	0.92***
	(0.03)	(0.15)	(0.03)	(0.14)	(0.02)	(0.10)	(0.02)	(0.10)
	(0.04)	(0.20)	(0.04)	(0.18)	(0.03)	(0.12)	(0.03)	(0.11)
Lag demand					0.11***	0.74***	0.10***	0.72***
					(0.01)	(0.08)	(0.01)	(0.07)
					(0.02)	(0.10)	(0.02)	(0.09)
Pop	0.05*	0.24***	0.045*	0.21**				
	(0.02)	(0.06)	(0.02)	(0.07)				
	(0.03)	(0.08)	(0.03)	(0.08)				
GDP per capita	-0.01**	-0.87	-0.008*	-0.65				
	(0.003)	(0.45)	(0.004)	(0.40)				
	(0.007)	(0.60)	(0.006)	(0.50)				
CAGR pop	1.98***	2.02**	1.85***	1.95**	1.24***	1.96**	1.20***	1.85**
	(0.40)	(0.85)	(0.38)	(0.80)	(0.32)	(0.78)	(0.30)	(0.75)
	(0.45)	(1.00)	(0.42)	(0.90)	(0.35)	(0.90)	(0.32)	(0.85)
CAGR GDP	-0.69	-1.9	-0.60	-1.8	-0.08	-0.53*	-0.07	-0.50*
	(0.52)	(0.21)	(0.50)	(0.20)	(0.09)	(0.28)	(0.08)	(0.27)
	(0.60)	(0.25)	(0.55)	(0.22)	(0.12)	(0.35)	(0.10)	(0.30)
Lag HHI	-3.14*	-4.68***	-3.00*	-4.50***	-2.63*	-1.76***	-2.50*	-1.70***
	(0.06)	(0.08)	(0.06)	(0.08)	(0.04)	(0.05)	(0.04)	(0.05)
	(0.08)	(0.12)	(0.07)	(0.11)	(0.06)	(0.07)	(0.05)	(0.06)
Delta freq	0.003***	0.03***	0.0028***	0.028***	0.004***	0.05***	0.0039***	0.048***
	(0.0004)	(0.01)	(0.0004)	(0.01)	(0.0005)	(0.01)	(0.0005)	(0.01)
	(0.0005)	(0.015)	(0.0005)	(0.014)	(0.0007)	(0.015)	(0.0006)	(0.014)
Delta freq comp	-0.001**		-0.0011**		-0.001**		-0.001**	
	(0.0003)		(0.0003)		(0.0004)		(0.0004)	
	(0.0005)		(0.0005)		(0.0006)		(0.0006)	
Age HSR	0.11**	0.57**	0.10**	0.55**	0.08**	0.28**	0.08**	0.27**
	(0.05)	(0.22)	(0.05)	(0.21)	(0.04)	(0.13)	(0.04)	(0.12)
	(0.06)	(0.28)	(0.06)	(0.26)	(0.05)	(0.15)	(0.05)	(0.14)
Travel time ratio	0.42**	0.58***	0.40**	0.55***	0.38**	0.67***	0.36**	0.65***
	(0.18)	(0.15)	(0.17)	(0.14)	(0.16)	(0.14)	(0.15)	(0.13)
	(0.22)	(0.20)	(0.20)	(0.18)	(0.18)	(0.16)	(0.16)	(0.15)
Trend	0.21*	0.19*	0.20*	0.18*				
	(0.11)	(0.10)	(0.11)	(0.10)				
	(0.13)	(0.12)	(0.12)	(0.11)				
Feeding HSR	-0.31**	-0.28***	-0.30**	-0.27***	-0.22**	-0.37***	-0.21**	-0.35***
	(0.14)	(0.08)	(0.13)	(0.08)	(0.09)	(0.07)	(0.09)	(0.07)
	(0.17)	(0.10)	(0.16)	(0.09)	(0.11)	(0.09)	(0.10)	(0.08)
Nr obs	363,327	129,596	363,327	129,596	363,327	129,596	363,327	129,596
R^2	0.53	0.65	0.52	0.63	0.67	0.83	0.66	0.82
MAPE	0.82	0.76	0.78	0.74	0.74	0.21	0.72	0.20
MAE	3,005	1,166	2,800	1,150	889	701	860	680

The clustered standard errors (second line in parentheses) are generally larger than the non-clustered ones, reflecting intra–city-pair correlation and heteroskedasticity in the residuals. This adjustment leads to more conservative inference by accounting for within-route dependence. After clustering, most coefficients retain their significance and signs, indicating that the core relationships are robust. Compared to non-clustered results, significance levels slightly weaken for a few variables—most notably the GDP coefficient in the aggregated M1 specification (from significant at 10% to insignificant), and a mild reduction in significance levels for *CAGR pop*, *Age HSR*, and *Travel time ratio*. Nonetheless, the majority of key variables, such as *Distance*, *Lag demand*, *Delta freq*, and *Feeding HSR*, remain statistically significant. Overall, clustering increases inference reliability without altering the substantive interpretation of the estimated effects.

By considering the most accurate model with the aggregate-carrier specification (following what we stated in Section 3.2), we test the model's performance demand in years 2018-2019 and compare

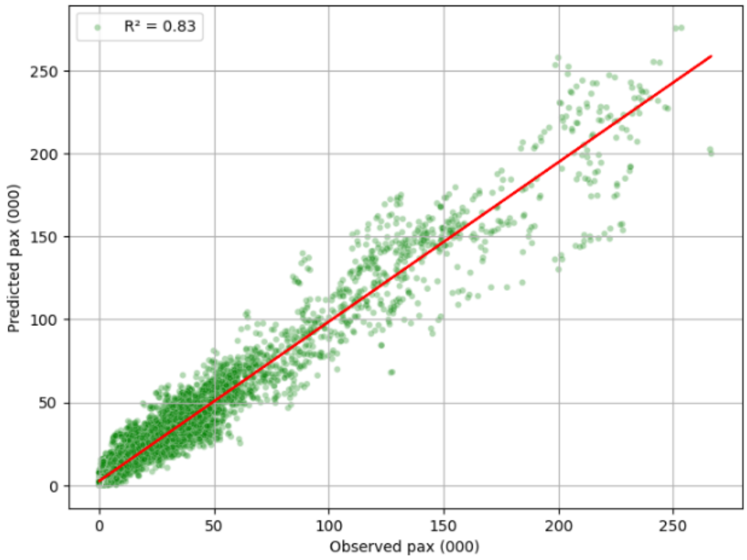


Fig. 1. Semi-Log OLS M2 aggregated model specification results using test set (2018-2019) for measuring the predictive performance. Results has been linearized for the representation.

the predicted passengers demand with the observed passengers demand (see Figure 1).

Additionally, Figure 2 illustrates the relative importance of variables considered in the predictive model. The four model specifications (M1, M2 with carrier and aggregated formulations) are compared to assess the significance of each variable. The color intensity reflects the normalized impact of each variable, with lighter shades indicating greater importance.

The importance of each variable in the plot is assessed based on the absolute magnitude of the estimated coefficients, normalized relative to the largest coefficient within each model. This approach allows for a comparison of the relative influence of different predictors on the dependent variable. The heatmap visualization highlights which variables exert the strongest effects, providing an indication of their relative impact[17].

In conclusion, it underscores the substantial influence of HSR presence and competitive dynamics on air travel demand. Variables related to HSR and its competition exhibit high levels of importance across different model configurations. This highlights the need and the pivotal role played by HSR data and competitive elements when modeling Chinese domestic air travel demand. By doing so, they can better anticipate shifts in passenger behavior and adjust their strategies accordingly, ensuring more precise forecasting and effective resource allocation in a rapidly evolving transport landscape.

To summarize, the analysis of the semi-log formulation models reveals significant insights into how different factors influence air passenger demand amidst HSR competition. Our analysis revealed a significant negative impact of HSR on air travel demand across our sample. The introduction of HSR routes initially led to a sharp decline in air travel demand, particularly pronounced during the early stages following route implementation. This finding underscores the disruptive influence

[17]It is important to note that this measure reflects the magnitude of the effect and does not directly indicate the amount of variation explained or the statistical significance of the coefficients. Therefore, the results should be interpreted as a ranking of variables by their relative influence rather than by predictive power or statistical certainty.

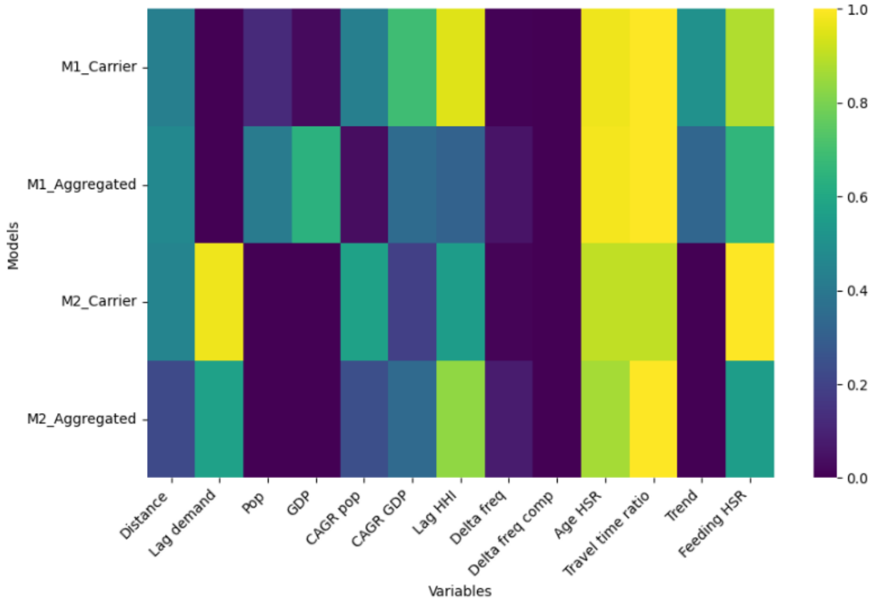


Fig. 2. Variables importance level across the four model configurations. Colors correspond to the relative importance of each variable, with lighter shades indicating higher importance. For variables not included in a model specification a 0 importance value has been assumed.

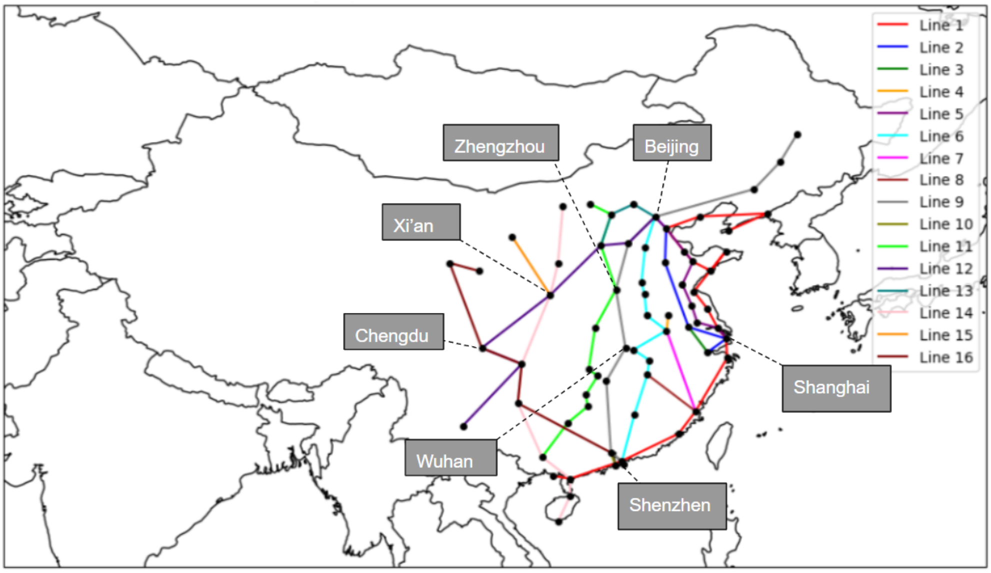
of HSR on air routes.

5. Case study: 2030 railway network expansion

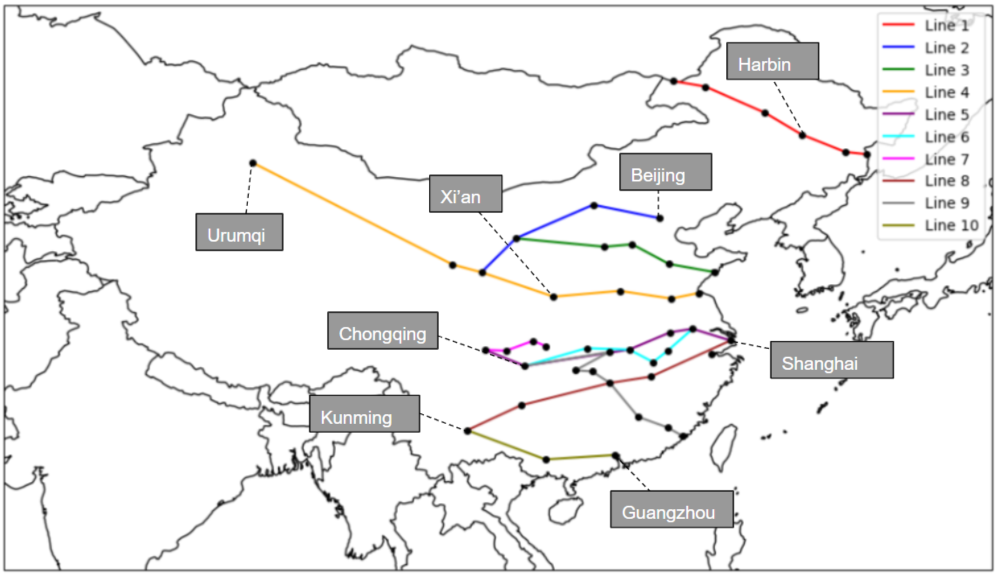
This case study examines the impact of the planned 2030 railway network expansion on transportation dynamics in China. Section 5.1 focuses on providing a preliminary evaluation regarding the changes in travel time resulting from the expansion of the HSR network. It compares the new travel times offered by HSR with those of existing air travel routes, highlighting the competitive advantages and potential shifts in transportation preferences. This analysis provides insights into how the expanded network will alter the accessibility and convenience of travel between cities. Section 5.2 explores the projected impact of the HSR expansion on future air travel demand, applying the forecasting methodology developed in Section 3.2.2. By analyzing trends and forecasting models, this section assesses how the introduction of new HSR connections is likely to affect air travel volumes in the next two decades. Together, these subsections offer an insights into the anticipated effects of the 2030 railway network expansion on travel times and air travel demand.

5.1. Comparative travel time assessment

The case study presented in this section focuses on the Chinese domestic HSR routes scheduled for opening in 2030, as shown in Figure 3.



(a) Vertical HSR connections to be implemented in 2030.



(b) Horizontal HSR connections to be implemented in 2030.

Fig. 3. Backbone HSR lines planned to be opened in 2030. Subplots divide the network lines into vertical connections (a) and horizontal connections (b).

In addition to applying our demand forecasting model to these new market connections, we conduct a preliminary accessibility evaluation. This evaluation compares land-side travel times, which reflect the ease with which potential passengers can reach airports and HSR stations. Given the intense competition between airports and HSR in China (Zhang et al., 2019a), ground travel time emerges as a crucial factor in passenger decision-making, alongside other considerations such as price, service frequency, and scheduling. The increasing competition of HSR is also related to its very high reliability combined with the fact that airports are often located far from the center of the city. For example, between Beijing and Nanjing (1000 km) the HSR travel time is about 3.5 hours, compared to 2 hours of air; however, the Nanjing airport is 47 km from the city center, whereas the HSR station is only 10 km from downtown. After factoring in this longer access distance, together with airport processing, passengers find the HSR service is very competitive and now on Beijing-Nanjing route it has the 60% of the market share. The reliability, frequency and comfort of HSR service create strong competition for most middle-distance trips.

We estimate multi-modal accessibility, which accounts for both automobile driving time and public transit options (following the work of Sun et al. (2021a))[18]. This composite indicator reflects the minimum travel time required for passengers to reach their destination, considering either driving or public transit, with the city center serving as the origin and destination in both the departure and arrival cities. By combining these modes of transport, this indicator provides a realistic measure of accessibility, capturing the ease with which passengers can reach an airport or HSR station using the available transportation infrastructure[19]. Figure 4 displays the total travel itinerary that the passenger is supposed to perform. We measure travel time assuming the passenger begins the journey from the city center, based on the premise that city centers typically concentrate the highest population densities and major touristic attractions[20]. This approach recognizes the consumer's utility or disutility in selecting air or rail transportation based on the location and connectivity of stations.

A HSR efficiency index in terms of accessibility score is calculated as $\frac{HSRtraveltime}{airtraveltime}$. It represents the comparative travel time advantage, with values lower than 1 indicate an HSR advantage over air travel, while values higher than 1 indicate an air travel advantage over HSR. Additionally, different dwell times (applied as penalization weights on the overall travel time) have been tested to simulate check-in waiting times at both airports and rail stations and they have been summed as part of the total travel time (refer to Koppelman et al. (2008),Moyano et al. (2018) and Wang et al. (2020a) for similar approaches). We tested several scenarios, with waiting times for HSR ranging from 30 to 60 minutes and waiting times for air ranging from 90 to 120 minutes. Therefore, for each travel from a city i to a destination city j and for each transport alternative (air vs rail), we can define the total travel time (city center-to-city center) t_{ij} along the path with the shortest possible time. It consists of two parts, namely the in-vehicle[21] (i.e., in-flight or in-rail travel time) t^V and waiting time at airports/stations t^W. Hence the total travel time t between any given city pair can be calculated as in Eq. 5.1:

$$t = t^V + t^W \tag{2}$$

[18]The proposed accessibility index is purely time-based and does not explicitly factor in the role of frequency.

[19]For travel time estimation, we integrate public transportation data from OpenStreetMap (OSM) and driving distance estimation with Open Source Routing Machine (OSRM), which is based on the road network encoded in OSM. These data are used to estimate car driving time and to extract public transit networks. For public transit connections, travel time is modeled as $\frac{distance}{50km/h}$.

[20]Assuming as reference point the city center allow us to minimize the computational time, without affecting the problem's scalability. However, this approach may present limitations, as it does not fully capture the spatial heterogeneity of urban areas. Further works could assume different points of interest and administrative levels (such as the working places) or assume a grid-based approach.

[21]Flight/HSR travel time t^V reflects the actual travel time spent on flights/trains and primarily depends on the distance between origin and destination as well as the operating speed of the flight/HSR.

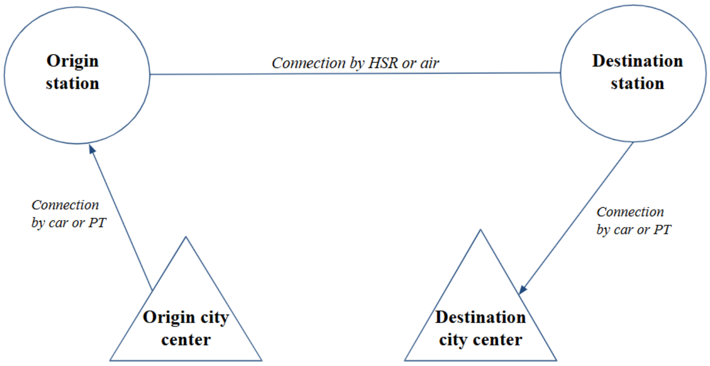
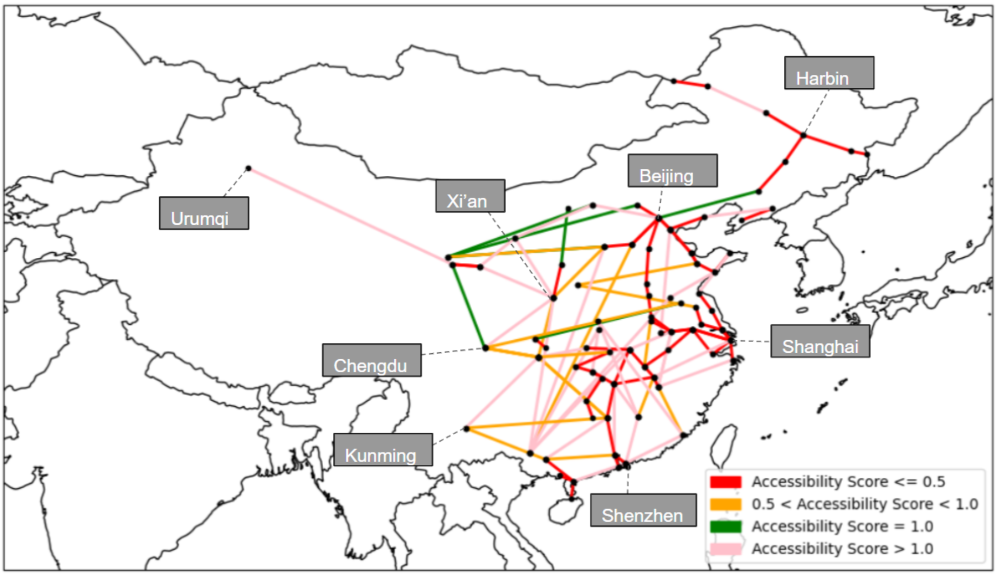


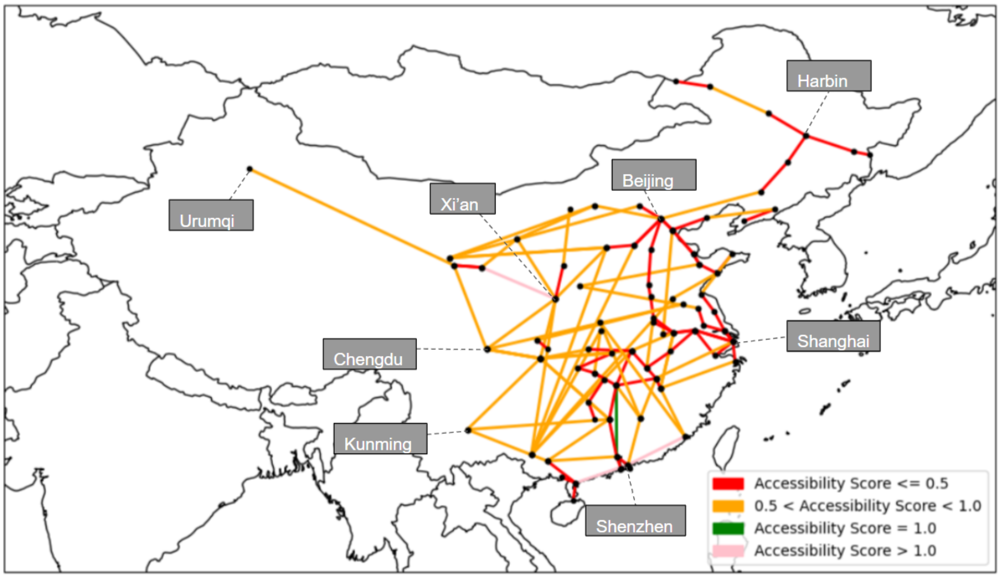
Fig. 4. Total travel itinerary for a passenger supposing to start and end the trip to the city center, either by HSR or air with the support of car or public transport for the segment city center-station, and vice versa.

Figure 5 shows comparative travel time scores among market pairs resulting from our analysis[22].

[22] Only figures displaying two scenarios have been reported in the current Section, for a more comprehensive investigation of all the different scenarios please see the Appendix.



(a) No dwell time.



(b) Dwell time 60 minutes for HSR and 120 minutes for air.

Fig. 5. Comparative travel times along the backbone HSR lines 2030, with different penalty time scenario. Subplots show: (a) No dwell time applied and (b) Dwell time of 60 minutes for HSR and 120 minutes for air.

5.2. *Air demand future trend*

To predict Chinese domestic air travel demand in 2030, we employ the forecasting model developed in Section 3. This model uses coefficients from the best-performing model, M2-aggregated, as identified in Section 4. We apply the model on the subset of cities that in 2030 will be connected by HSR (as shown in Figure 3) and that in the past years are already connected by air transport.

For the real-world data that will be unavailable from 2025 on, we adopt various elaboration methods regarding the type of data. For data related to aviation scheduling (such as frequency supply and the number of seats offered by carriers), we conduct a scenario analysis, simulating a trend projection under the assumption that the future trend will follow the historical growth trend. For socio economic variables we apply future projections derived from the most extant literature.

Relatively to aviation data, to predict air demand in 2025 we use values of frequency and market concentration at 2024[23]. After that, to predict demand for future years until 2030, we apply an increase parameter of about 5% for flight supply and 2% for market concentration[24]. Starting from 2030 (the year in which the direct HSR connection will be introduced between those cities), we apply a decrease parameters of about -3% for flight supply and -2% for market concentration[25]. This historical data provides insights into how aviation variables such as frequency and market concentration (proxied by HHI variable) have evolved in the presence or absence of non stop HSR connection and how they had an impact on the travel time advantage and passengers' utility. By applying the same percentage parameter to our new sample of cities, we create a scenario reflecting the historical trend behavior.

The data projections for socio-economic variables are based on the shared socioeconomic pathways scenario (SSPs) (Chen et al., 2020; Wang and Sun, 2022; Wang et al., 2022). The SSPs are defined as a set of future pathways of societal development that describe five alternative outcomes of trends in demographics and economic development, provided by the International Institute for Applied System Analysis (IIASA). From the methodological perspective, we elaborate a framework based on the average population and GDP per capita values of the five scenario. Table 5 provides a comprehensive overview of the five scenarios and their different characteristics.

Table 5. Demographic assumptions in China under SSPs. In SSP4, assumptions for education depend on the provincial development level.

Scenarios	**Fertility**	**Mortality**	**Migration**	**Education**	**Policies**
SSP1	Low	Low	Medium	High	Ineffective fertility policy
SSP2	Medium	Medium	Medium	Medium	Effective two-child policy
SSP3	High	High	Low	Low	Effective fully open policy
SSP4	Low	Medium	Medium	H/M/L	Ineffective fertility policy
SSP5	Low	Low	High	High	Ineffective fertility policy

Figure 6 illustrates the projected increase in air travel demand for the year 2025. The increments reflect typical changes observed in aviation scheduling and market concentration in the absence of non stop HSR itineraries, but with only connecting HSR itineraries available between cities. In this scenario, air demand is predicted to exhibit an increase ranging from 5% to 50%, approximately. In particular, long haul itineraries will experience a higher demand increase. Interestingly, even short-haul itineraries, which are typically the most vulnerable to HSR competition, show an increase in air demand in this scenario, albeit at a lower rate than long-haul routes. This may suggests that while 1-stop HSR connections may appeal to some passengers, they do not offer sufficient utility

[23] Those variables in M2-aggregated model formulation are used with 1 year lag.

[24] These parameters values have been extrapolate by the historical growth in cities that are connected by HSR only with at least 1 stop itinerary.

[25] These parameters values have been extrapolate by the historical decrease in cities that are connected by HSR not only with 1 stop connected itineraries, but also with non stop itineraries.

to prompt a widespread shift from air travel. This result can be explained by considering factors inherent to the current travel context. The forecasting model indicates a negative coefficient for the feeding HSR variable, which would suggest a decrease in air demand when there is strong HSR connectivity between the origin and destination stations. However, in this scenario, the origin-destination itinerary for air travel is already a one-stop route, and if one-stop rail itinerary can be competitive with a non-stop air itinerary (even without showing a full-substitution effect of mode of transport), it is less likely that passengers would opt for a two-stop rail journey over a non-stop air journey. In conclusion, the strong negative power of the HSR feeding variable against the air demand is mostly effective regarding non-stop HSR connections.

Figure 7 showcases the decrease in air travel demand following the introduction of non stop HSR connection. The model predicts a large shift from air to rail transport as smoother and faster HSR options become available, leading to a decrease higher than 90% of air travel demand in certain city pairs. These city pairs, which are projected to experience a large shift from air travel to HSR, have been labeled according to the year in which this transition is expected to occur. Notably, our analysis reveals that the shorter the itinerary, the sooner the demand shift effect is likely to manifest.

By comparing the predicted demand with the two development scenarios (Figure 6 and Figure 7), we highlight the impact of new rail infrastructure on air travel patterns. It is important to note that the city pairs experiencing more than 90% drop in air travel demand (with respect to historical years level) are the same ones that, in our comparative travel time analysis (see Section 5.1), were identified as benefiting most from HSR. In that analysis, these city pairs were projected to gain a clear advantage with HSR across various scenarios of dwell times. This alignment between the time advantage analysis and the predicted demand shifts highlights the reliability of our model and the transformative impact HSR will have on certain air markets.

Both figures offer a clear visual representation of these predicted shifts, providing critical insights into how the integration of HSR will reshape regional transportation dynamics. The prediction of a large shift in demand from air to HSR in specific markets signals a potential end to air travel in these routes, emphasizing the importance of such predictive analysis in understanding and planning for the future of transportation.

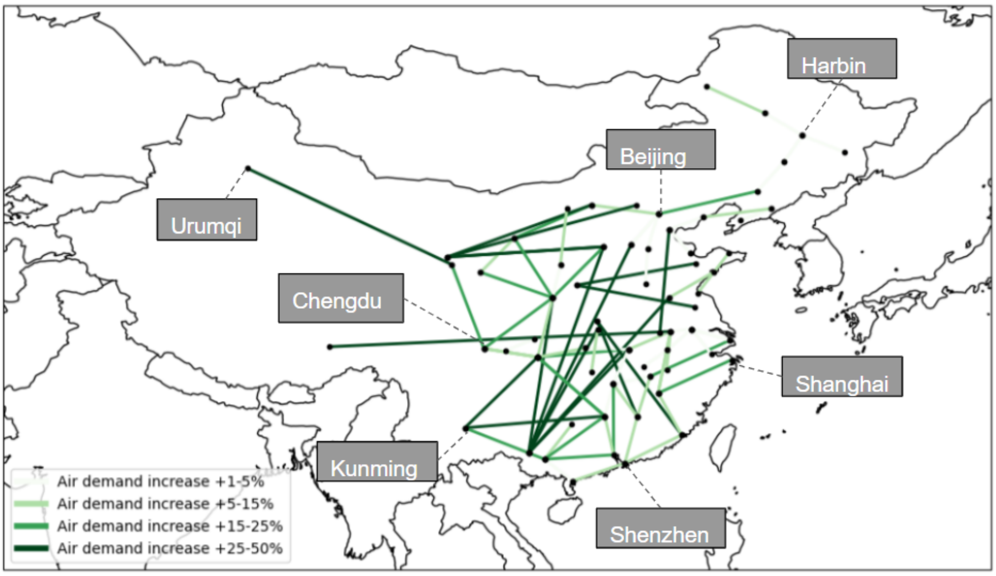


Fig. 6. City pairs connection with color differentiation based on the air demand increase in 2025, without the new set of HSR lines opening.

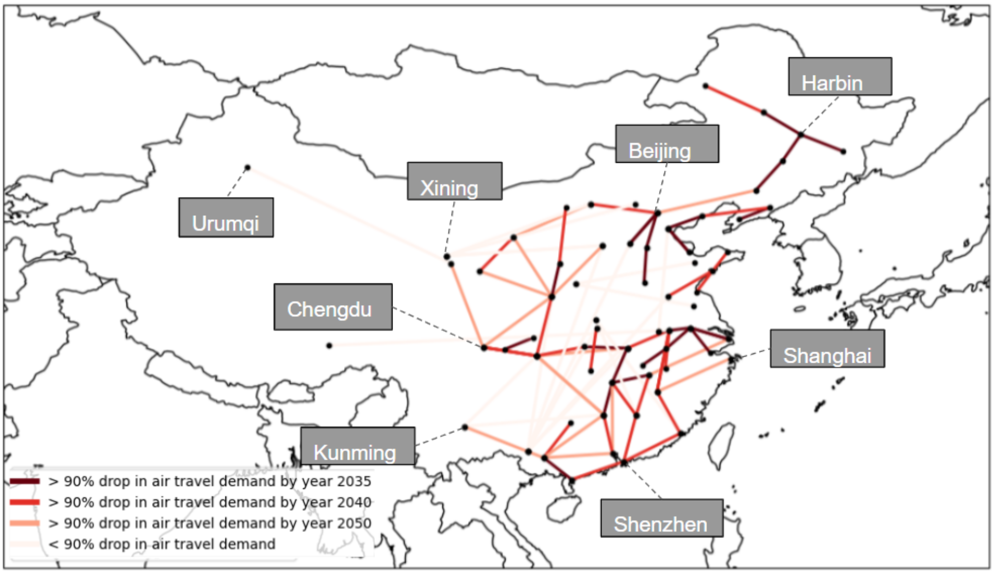


Fig. 7. City pairs connection with color differentiation based on the air demand decrease and disappearing during the interval 2030-2050, following the HSR lines opening.

In the context of analyzing the shift from air travel to HSR, a violin plot in Figure 8 displaying the relation between distance and the year of total demand shift provides critical insights into the relationship between route length and the timing of this transition. The plot reveals how city pairs with varying distances are expected to experience a complete shift in travel demand from air to HSR over different years. This relationship is visually represented by the shape and distribution of the violins, where denser sections indicate a higher concentration of city pairs within specific distance ranges. Insights gained from this analysis show and confirm that shorter routes tend to experience a total demand shift earlier, as HSR's competitive advantage is more pronounced over shorter distances. The plot also allows us to observe trends and clusters, indicating which air markets are most vulnerable to disappearing sooner due to the introduction of HSR. This visualization is instrumental in strategic planning, enabling transportation policymakers to prioritize infrastructure development in regions where the shift from air to rail is expected to be most significant.

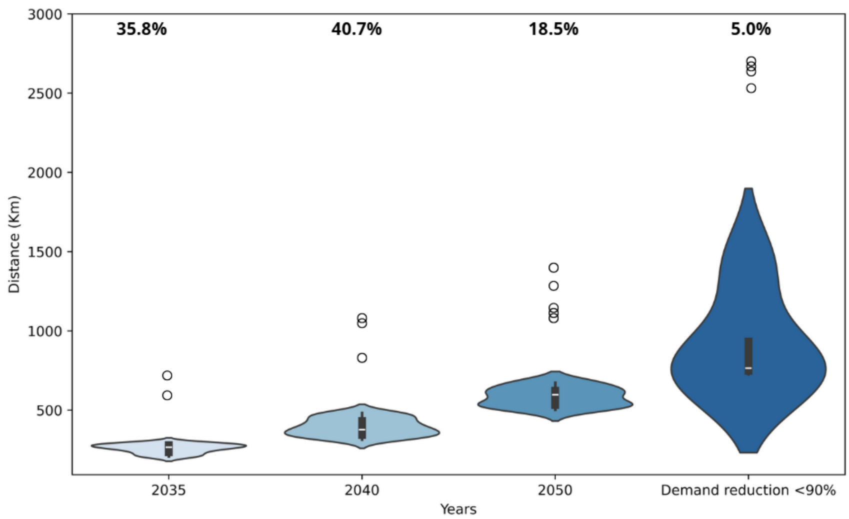


Fig. 8. Distribution of origin–destination pairs by distance category experiencing more than 90% air demand reduction by year. Percentages above each violin indicate the share of OD pairs within each category.

Beyond demand shifts, the substitution from aviation to HSR also carries important implications for carbon emissions and broader sustainability outcomes. While our model documents that certain OD pairs may experience declines of more than 90% in air travel following nonstop HSR entry, the resulting climate benefit depends on several factors, including the relative emissions intensities of air and rail, the electricity mix powering the rail system, and the embodied emissions associated with infrastructure construction. Recent evidence for China suggests that HSR openings can contribute to reductions in city-level carbon emissions through indirect channels such as enhanced green innovation and greater resilience of environmental investment (Wang et al., 2024). Regarding direct operational emissions, a growing body of empirical work shows that HSR is substantially more carbon-efficient than aviation on a per passenger-kilometer basis. Multiple studies estimate that HSR emits materially less CO per pkm than domestic air travel in China (Yuan et al., 2023; Wan et al., 2023; Wang et al., 2023), with commercial aviation producing several times the emissions intensity of HSR during operations (Strauss et al., 2021; Yu et al., 2021). However, assessments that incorporate full lifecycle emissions including construction and infrastructure reach more heterogeneous conclusions. While some studies find that HSR retains a carbon advantage on high-demand corridors, others suggest that the emissions payback period can be lengthy and corridor-specific, potentially extending over several decades depending on demand levels and construction intensity (Kortazar et al., 2023; Takebayashi and Yamaguchi, 2024). In the context of the present study, these findings imply that large-scale substitution from air to rail is likely to reduce carbon emissions on many OD pairs, particularly those with high demand and frequent air services. Nevertheless, the magnitude and timing of these benefits are context-dependent. Importantly, our contribution does not hinge on establishing the universal environmental superiority of HSR, but rather on documenting how demand reallocation unfolds across markets, providing a foundation upon which environmental and welfare assessments can be layered in future work.

5.3. Policy Implication

The findings of this study carry important implications for transport policy and strategic planning in China and other countries undertaking large-scale HSR expansion. By integrating robust econometric forecasting with socio-economic and transport network variables, this research moves beyond the ex-post implementation analyses found in the literature and offers a dynamic, forward-looking perspective on the timing and magnitude of air–rail demand substitution. The identification of distance-specific thresholds and early-phase substitution effects provides a quantitative foundation for proactive policy design, allowing decision-makers to anticipate rather than react to intermodal shifts. The analysis shows that the competitive pressure of HSR is strongest on routes below approximately 550 km, where air services are likely to become structurally unviable by 2050. This finding has direct implications for airline network optimization. Airlines and regulators should jointly plan for hub downsizing and fleet adaptation, progressively reallocating capacity from short-haul to medium- and long-haul markets. Smaller regional jets serving short domestic routes may become redundant, while wide-body or fuel-efficient narrow-body aircraft could be deployed to strengthen interprovincial and international connectivity. Policymakers can facilitate this transition through slot reallocation mechanisms that prioritize strategic routes and through incentives that encourage carriers to redeploy capacity in line with evolving demand patterns. At the same time, the results emphasize the importance of intermodal integration policies to enhance complementarity between air and rail services. Rather than competing for overlapping markets, both modes can be integrated within a coordinated mobility framework. Policy instruments such as shared terminal infrastructure, synchronized scheduling, and unified ticketing platforms can enable smooth air–rail transfers, transforming major airports into multimodal hubs that support long-distance connectivity while maintaining efficient feeder links. The predictive modeling framework presented here can assist authorities in identifying city pairs where such integration would yield the greatest network benefits, both in terms of capacity use and passenger convenience.

The projected decline in short-haul air demand also raises concerns about regional equity and accessibility. Smaller airports serving short domestic routes may experience significant traffic losses, leading to reduced connectivity for secondary cities. To mitigate this risk, transport policy should promote HSR feeder networks and targeted regional air service programs in areas not yet connected by rail. Such measures would ensure that the benefits of HSR expansion are distributed more evenly across regions, preventing the emergence of accessibility gaps and maintaining socio-economic cohesion. More broadly, the restructuring of travel demand brought about by HSR expansion presents an opportunity to rethink infrastructure investment priorities. Airports located along major HSR corridors can be repositioned as intermodal nodes that integrate rail, air, and urban transit systems, promoting a more efficient and sustainable use of existing capacity. Aligning investment strategies with this integrated vision would help avoid redundant infrastructure expansion and support national objectives for carbon reduction and sustainable mobility.

Because the substitution effects identified in this study are time-dependent and regionally differentiated, continuous demand monitoring and adaptive policymaking are essential. The econometric forecasting framework developed here can serve as a decision-support tool to simulate alternative development scenarios, assess intermodal complementarities, and inform both infrastructure sequencing and regulatory design. Embedding such predictive models within transport policy processes would represent an important step toward evidence-based and anticipatory governance of intermodal mobility systems. Beyond China, the insights derived from this analysis contribute to the broader literature by demonstrating how predictive modeling can inform strategic, preemptive policy interventions in air–rail markets. For emerging economies planning major HSR networks, the Chinese experience underscores the importance of early coordination between transport modes, adaptive airline restructuring, and equity-oriented planning to ensure that the transition toward high-speed rail fosters both efficiency and inclusiveness in national transport systems.

6. Conclusions

In this study, we developed a demand forecasting model to analyze the impact of HSR expansion on air travel demand in the Chinese domestic context. The analysis particularly focused on the HSR lines opening by 2030 and aims to identify the aviation markets most likely to experience pressure following the introduction of these new rail connections.

The analysis employs a robust econometric framework that integrates detailed historical scheduling and traffic data with high-quality socio-economic projections. Within this forecasting framework, we assume that the city-pair air network topology remains fixed through 2050, meaning that we do not simulate the endogenous entry or exit of air routes. Instead, frequencies and seat capacities on existing routes are projected coherently based on historical growth patterns. This modeling choice is deliberate, as a full treatment of airline network formation would require a structural framework jointly accounting for airline route choice, slot constraints, airport policies, and demand thresholds, which lies beyond the scope of the present paper. Our focus is therefore on the dominant mechanisms driving mode substitution—namely travel time, frequency, capacity, and accessibility. HSR travel times for lines planned to open by 2030 are derived from official planning documents and conservative operational assumptions, explicitly incorporating access and egress components to reflect realistic door-to-door travel times. Importantly, we do not assume further exogenous increases in HSR speeds beyond what is currently planned, given the absence of official projections. This ensures that the estimated substitution effects are driven by network expansion rather than optimistic performance assumptions.

The forecasting analysis reveals, with an accuracy ranging from 0.53 to 0.83, that HSR exerts significant competitive pressure on air travel, with new rail routes leading to notable reductions in air demand, particularly in markets where HSR offers a more convenient alternative due to the lower travel time. In particular, the negative coefficients of feeding HSR variable, ranging from -0.21 to -0.37, highlight that the higher the HSR connectivity, the lower the air demand, meaning that often a connecting HSR itinerary is perceived as more convenient than non-stop air itinerary. Moreover, the positive coefficients of travel time ratio and age HSR variables, ranging from 0.38 to 0.67 and from 0.08 to 0.57 respectively, show that the lower the HSR travel time, the lower the air demand and the switching demand effect from air to rail is higher during the first phase of rail introduction. The predictive model has been completed also with the inclusion of aviation-related variables, such as the lagged demand, the market concentration index, the percentage increase in frequency and socio economic components, namely population and GDP, all showing positive coefficients on the air demand.

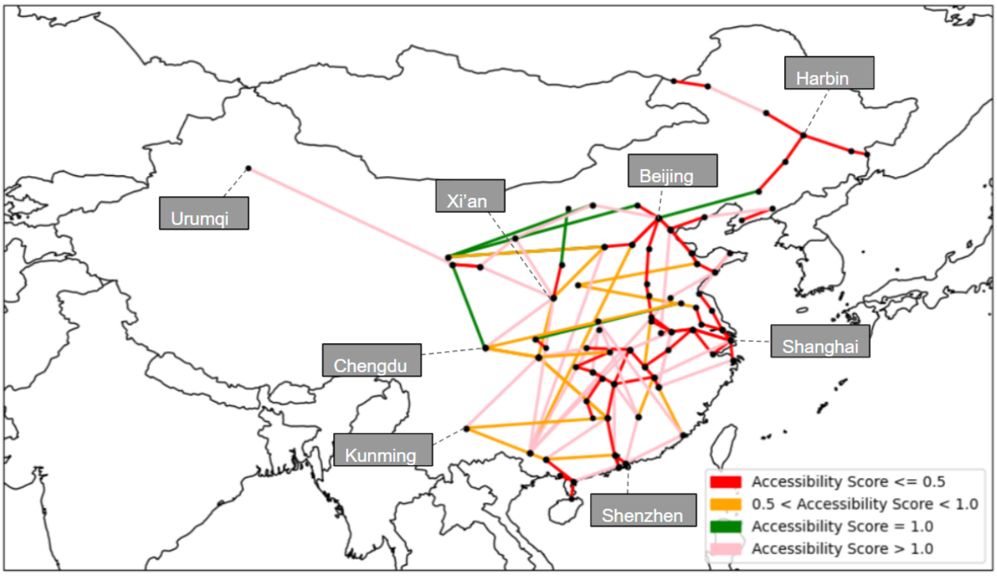
Our application of the demand forecasting model to the set of cities that will be connected by new HSR connections starting from 2030 reveals a profound shift in air travel dynamics, particularly for routes under 550 km. In the scenario analysis for 2025, the landscape of domestic air travel reflects a period of growth, before the impact of HSR introduction is realized. Our forecasting results show that, in absence of direct HSR lines (only 1 stop rail connection is available), air travel across the subset of city pairs analyzed is expected to increase, with different growth rates. Quantitatively, this translates into a projected increase in air travel demand ranging from 5% to 50%, depending on the specific route characteristics and socio-economic conditions. Long-haul itineraries, in particular, are expected to experience the most substantial demand growth. For instance, routes exceeding 1500 km are likely to see demand increases closer to the upper end of this range, around 40% to 50%. This growth reflects the continuing preference for air travel on longer routes, where the absence of direct HSR competition allows airlines to capitalize on the growing population and economic activities. Nevertheless, by 2050 these shorter routes are projected to lose the majority of air travel demand as HSR becomes the dominant mode of transportation and likely for the airlines there will be not anymore convenient operate those itineraries. The speed, convenience, and city-center accessibility offered by HSR make it a highly attractive option for travelers. This shift not only marks a change in domestic travel patterns but also raises significant strategic challenges for airlines to adapt to this new competitive landscape, which may need to adapt their business or change their network to remain competitive.

These results provide a forward-looking perspective for policymakers and transportation planners, highlighting the need for strategic planning in infrastructure investment, airspace management, and intermodal transportation integration. Understanding the timing and extent of demand shifts will allow for more informed decisions, optimizing the overall efficiency and sustainability of China's transportation network. This study also serves as a valuable reference for other emerging markets where similar HSR developments may be planned, offering insights into the potential future dynamics between rail and air travel.

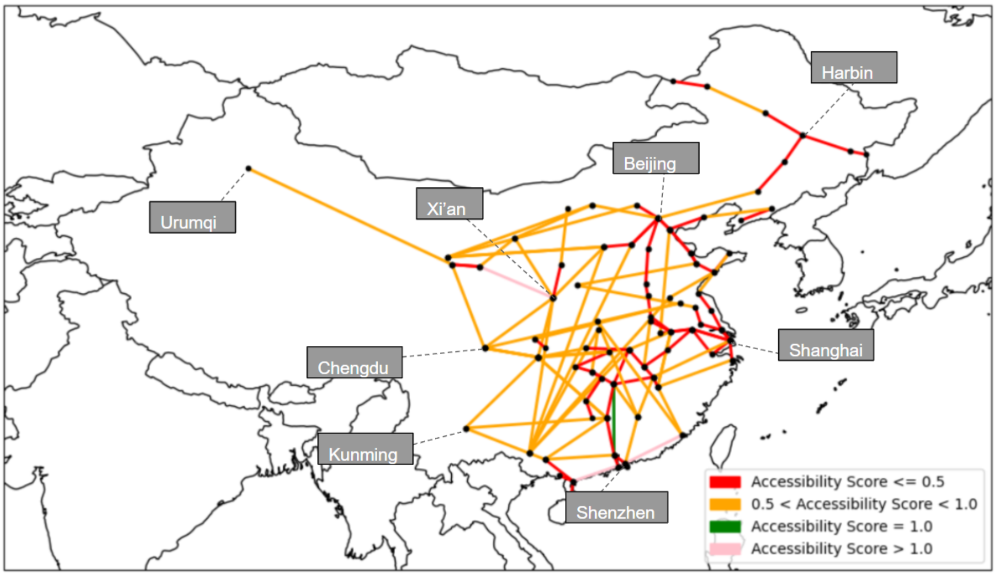
As HSR continues to expand, particularly in fast-evolving markets like China, the insights provided by this study can guide strategic planning, enabling stakeholders to better manage the transition from air to rail travel and optimize the allocation of resources to meet the changing demands of travelers. The forecasting model developed in this study is crucial not only for understanding the potential shift in travel preferences but also for proactively designing policies that ensure the long-term sustainability and competitiveness of both HSR and air travel. By anticipating these shifts, transportation planners can create a more resilient and adaptable transportation network, reducing the potential for economic disruptions and enhancing the overall travel experience for passengers.

While this study provides comprehensive insights into the impact of HSR expansion on air travel demand in China's domestic market, it is important to acknowledge limitations and potential improvements that could be addressed in future research. First, from a conceptual standpoint, one limitation lies in the assumptions made about competitive dynamics within the aviation industry and passenger travel behavior. While the model effectively captures the competitive pressure exerted by HSR on air travel, it assumes that travelers consistently choose the most time-efficient mode of transport and that airlines do not respond with alternative strategies, such as enhancing brand loyalty or offering frequent flyer programs. Second, from a methodological perspective, the model's reliance on long-term data projections poses limitations. Predictions spanning several decades do not account for potential disruptions, such as economic downturns, unforeseen technological advancements, or other unexpected events that could alter demand dynamics. Future research could extend the analysis by systematically exploring how different factors—such as socioeconomic pathways, projected air supply, market concentration, and HSR network connectivity—affect air travel demand. Despite these challenges, the current study provides a crucial foundation for understanding evolving air–rail interactions and offers valuable insights for policymakers, transportation planners, and the aviation industry.

7. Appendix

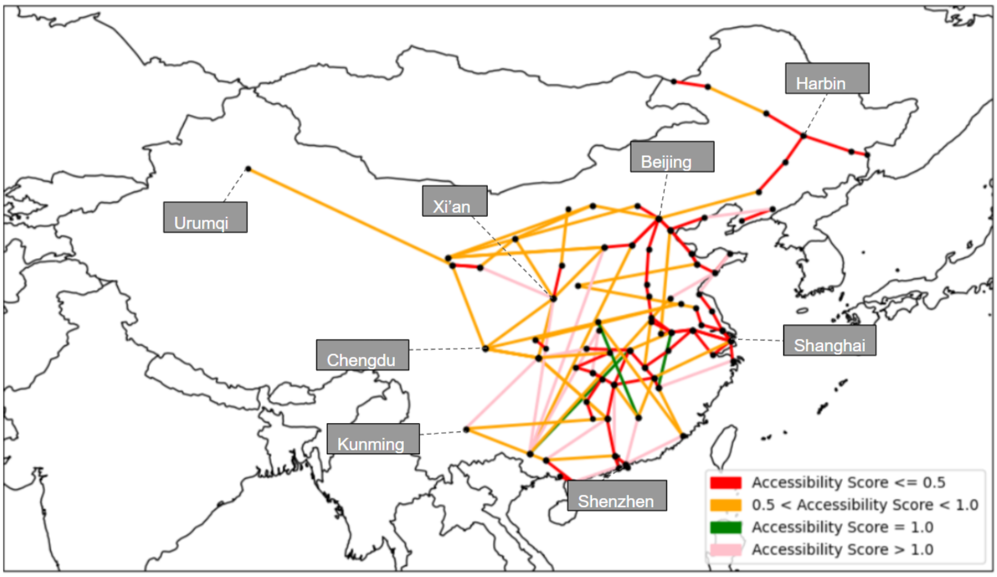


(a) No dwell time.

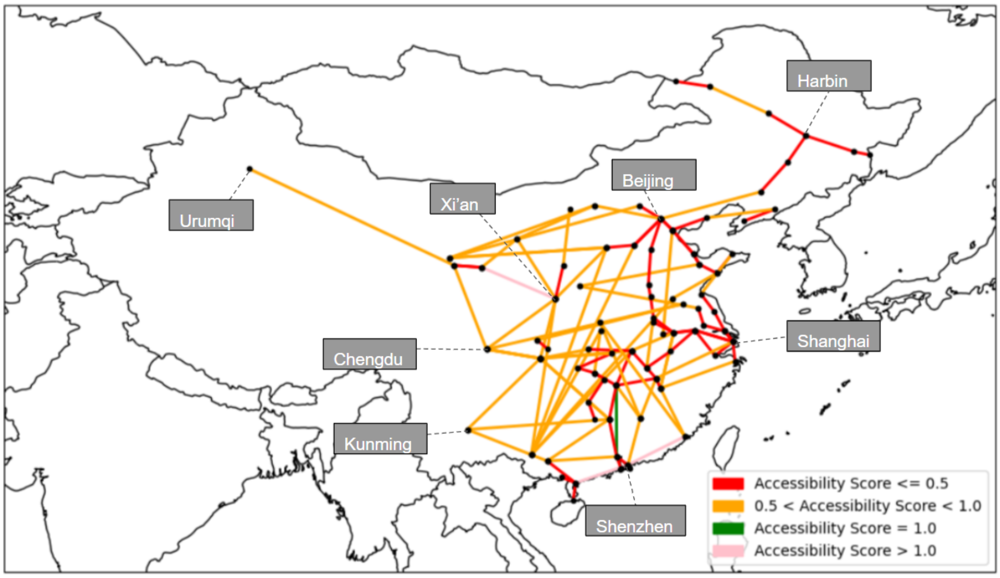


(b) Dwell time 30 minutes for HSR and 90 minutes for air.

Fig. 9. Comparative travel times along the backbone HSR lines 2030, with different penalty time scenarios. Subplots (a) and (b) show: (a) No dwell time applied; (b) Dwell time of 30 minutes for HSR and 90 minutes for air.

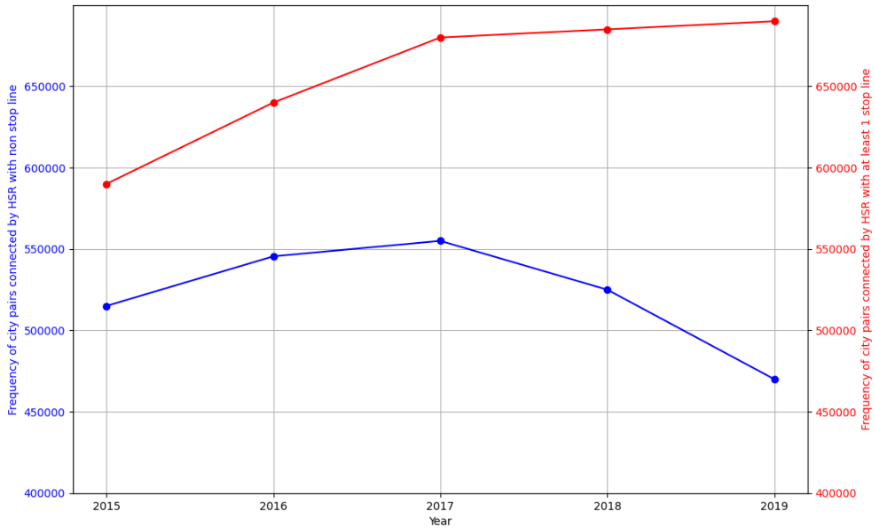


(a) Dwell time 60 minutes for HSR and 90 minutes for air

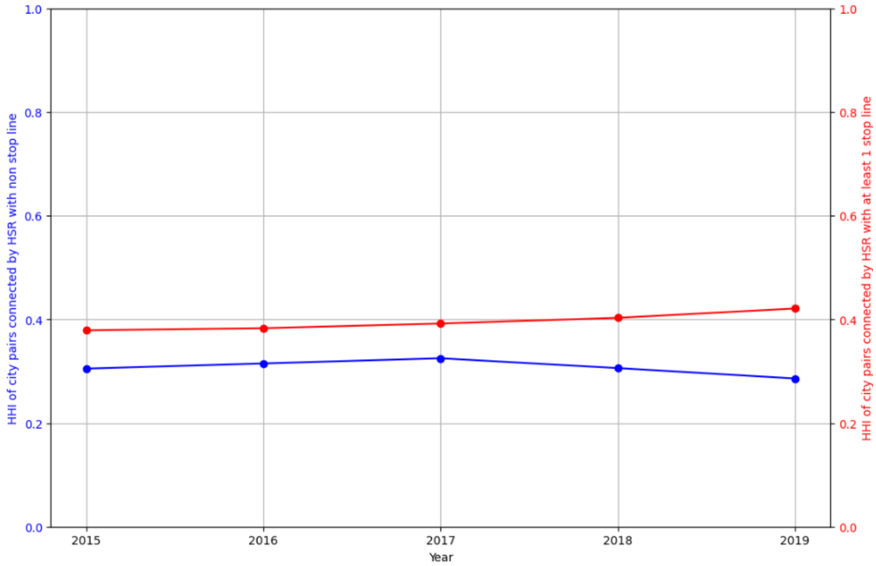


(b) Dwell time 60 minutes for HSR and 120 minutes for air.

Fig. 10. Comparative travel times along the backbone HSR lines 2030, with different penalty time scenarios. Subplots (a) and (b) show: (a) Dwell time of 60 minutes for HSR and 90 minutes for air; (b) Dwell time of 60 minutes for HSR and 120 minutes for air.



(a) Frequency historical growth from 2015 to 2019.



(b) HHI historical growth from 2015 to 2019.

Fig. 11. The plots show the historical evolution of frequency and market concentration (HHI) over the period 2015-2019 in two different scenarios: blue lines display the growth of city pairs also connected with non stop HSR line, red lines display the growth of city pairs also connected with at least 1 stop connecting HSR line.

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