Barriers in the Sky

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Abstract

This paper investigates the economic impacts of inefficiency in the transport network, using China's restrictive airspace as a case study. China's commercial airlines are limited to only 20% of its airspace, resulting in an average route curvature of 17% — compared to 5% in the U.S. and Europe. Using route curvature as a direct inefficiency measure and an IV estimation strategy, we find that increased route curvature raises airfares, reduces flight frequencies, increases delay rate, and reduces aero-connected city pairs. These inefficiencies cascade into broader economic costs, hampering intercity activities including personal travel, population migration, cross-city corporate investment, and patent collaboration.

Key words: Transportation network; Airline; Airspace regulation; Connectivity

JEL classification: O18, R11, R12, R42

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1 Introduction

Few inventions better embody the age of globalization than the airline network. Today, people and cargo are transported across the globe at unprecedented speeds and historically low costs. A key advantage of air travel is an airspace free of any physical barriers, allowing aircraft to follow the most efficient direct routes. However, flight paths do not often go straight — a fact that is often overlooked.

Consider two airline routes in China as an example: Shanghai to Zhangjiakou (1,205.1 km direct distance) and Chongqing to Shijiazhuang (1,205.4 km direct distance). Despite their near-identical direct distances, the route curvatures—measuring deviations from the straight-line path—differ significantly: 49.9% for the Shanghai-Zhangjiakou route versus 4.8% for the Chongqing-Shijiazhuang route. This means the Shanghai-Zhangjiakou route averages an additional 543 kilometers, making it nearly one-third longer than its counterpart.

The stark route differences in these examples cannot be attributed to common factors like weather conditions, bird strikes, or air traffic management. Instead, they highlight a critical yet often overlooked source of inefficiency in transportation networks: politics. National security regulations, geopolitical risks, and other political factors frequently lead to suboptimal transportation networks, affecting transportation industry dynamics and generating economic and welfare losses. While extensive research has documented welfare gains from transportation connectivity or the extensive margin of transportation networks (Faber, 2014; Bahar et al., 2023), particularly Campante and Yanagizawa-Drott (2018)'s work on airline connectivity, less attention has been given to the economic impact of inefficient route design, or the "quality" of the transportation networks. A key empirical challenge lies in measurement: How can we quantify route inefficiency? More specifically, how do we identify optimal counterfactual routes for comparison?

The airline network provides a unique setting to study the inefficient design of transportation networks for two main reasons. First, route curvature provides a direct and intuitive measure of inefficiency. Unlike land transportation, where optimal routes are shaped by multiple physical barriers such as mountains and rivers, air travel can be benchmarked against the great circle distance—the shortest path between two points on a sphere. While individual flights may deviate from this ideal due to "random" factors like weather or air traffic control, persistent route curvatures typically reflect regulatory constraints. Second, the airline

industry is one of the most heavily regulated sectors globally. Governments exert significant control over route establishment, airline formation, and market access through strict licensing and operational requirements. The impact of such regulations on route efficiency is evident in several recent examples: Argentina's pre-2016 mandate that almost all domestic flights pass through Buenos Aires caused substantial detours. The Russia-Ukraine war has forced EU and US carriers to avoid Russian airspace, resulting in longer trans-Pacific and trans-Atlantic routes. Similarly, during the 2017 Qatar diplomatic crisis, several Middle Eastern nations prohibited Qatari aircraft from accessing their airspace, further disrupting regional flight patterns.

In this paper, we use the unique regulatory environment of China—the world's second-largest civil aviation market,[1] yet operating under exceptionally restrictive airspace controls—to empirically investigate how airspace regulations shape the airline industry. While developed regions like the U.S. and Europe have progressively liberalized their airspaces since the 1970s, China maintains stringent military control, with 80% of its airspace under air force jurisdiction, and commercial routes can only use the remaining 20%. In contrast, commercial flights can use more than 80% of the airspace in the U.S..[2] A direct outcome is that the average curvature of China's airline routes is 17%,[3] much higher than the 5% observed in the U.S. and Europe.[4] This translates to an additional 164km of flight distance or 14 more minutes of travel time for an average-distance trip in mainland China. We then examine the impact of airspace regulation on airfares, flight frequency, inter-airline competition, and flight delay rate. Furthermore, we analyze how these regulatory impacts cascade into broader economic outcomes, such as inter-city economic activities, including personal travel patterns, population migration, cross-city corporate investment decisions, and patent collaborations.

To empirically investigate the impact of airspace regulation, we collect novel data from Flightradar24 to determine airline routes and measure airspace regulation in mainland China. For each flight, latitude and longitude coordinates are reported every 10 to 30 seconds. This allows us to map out each flight's route and then calculate the actual flight distance and the curvature of the airline route. We use the flight prices and carrier information in September 2019 from Ctrip.com, China's leading online travel agency. We use four proxies for inter-

[1] In 2019, the annual revenue for the airline industry in China was 154.27 billion USD.

[2] Source: Sina Finance

[3] The curvature of an airline route is defined as the percentage of the additional distance that the plane needs to fly, compared to the shortest possible distance (great circle distance).

[4] Source: Chinese People's Political Consultative Conference Website

city economic activities in 2019: the online search index (i.e., Baidu index), which measures annual searches of one city's name by users from another city; the Weibo mobility index, which measures annual travel frequencies of social media users between cities; cross-city corporate investment; and cross-city patent collaborations.

A key endogeneity concern stems from omitted variable bias: cities with greater political and economic significance may face higher levels of airspace regulation, as they are more likely to have nearby military bases (e.g., Beijing). Additionally, airlines may have incentives to lobby for straighter routes between major cities. Though balance tests confirm that airline route curvatures are not correlated with characteristics of departure and arrival cities, including GDP and population, we further address the endogeneity concerns using an instrumental variable (IV) method. The first IV leverages established airline routes from 1995 or earlier to predict the shortest route connecting two cities that were not connected in 1995.[5] Similarly, the second IV uses the average curvatures of the five nearest routes established in 1995 or earlier to predict the curvatures of post-1995 routes. Intuitively, because applying for new airspace is extremely costly, carriers will rely heavily on "free-riding" the existing routes.[6] Since the IVs are constructed using routes established in or before 1995, our IV regressions focus exclusively on city pairs that were unconnected in 1995 but became connected by 2019, rather than on the more prominent city pairs that were already connected by 1995. We confirm the robustness of our results across all outcome variables within this subsample. Furthermore, we include fixed effects for both departure and arrival cities to account for city-level characteristics.

Our instrumental variables provide two key advantages: First, they predict exogenous curvatures of existing airline routes between 1995 and 2019, allowing us to estimate the impacts on route frequency (intensive margin). Second, they predict potential curvatures of routes not yet established by 2019, enabling analysis of how exogenous curvatures influence new route creation (extensive margin).

Our results indicate that greater curvature of a specific route is associated with: (1) higher airfares for an average economy seat; (2) fewer weekly flights available on the route; (3) higher flight delay rate.

[5]The airline route data in 1995 is the earliest year for which such data is available.

[6]It's worth noting that airline routes have remained nearly unchanged since 1995, as the airspace available for commercial flights rarely changes. About 95% of routes established in 1995 or earlier still have the same scheduled airline route today.

We then move on to empirically verify the broader economic consequences of airspace regulation, using the online search index, travel frequencies of social media users, cross-city corporate investment, and cross-city patent collaboration. We confirm that all four economic activity measures decrease significantly as the curvature of airline routes between city pairs increases. This suggests that airspace regulation indeed has broader negative impacts on economic activities across cities. Using the predicted curvatures based on our IVs, we find that exogenous curvature also significantly reduces the probability of new routes being created between two cities by 2019, suggesting that airspace regulations substantially limit inter-city connectivity. A counterfactual analysis reveals that if China were to reduce its airspace regulation to the U.S. level, approximately 5% more city-pairs would become connected.

Our study contributes to the growing literature on the economic impact of transportation infrastructure, which has primarily focused on the economic impacts of whether transportation infrastructure is connected (i.e., the extensive margin), while paying less attention to the quality of the connection (i.e., the intensive margin). For instance, recent research has examined the effects of road or railway connections on market access (Banerjee et al., 2020; Herzog, 2021), immigration (Sequeira et al., 2020), economic growth (Faber, 2014; Banerjee et al., 2020; Dong et al., 2021), suburbanization (Baum-Snow, 2007; Baum-Snow et al., 2017), urban form (Duranton and Turner, 2012), and knowledge diffusion (Dong et al., 2020; Bahar et al., 2023). This paper uses China's airspace regulation as a case study to show that the "quality" of the connection has significant impacts not only on the airline industry itself but also on broader economic outcomes. We find that city-pairs with a "low-quality" connection (i.e., with higher airline route curvature) have weaker economic connections, as reflected by cross-city travel, corporate investment, patent collaborations, and migration intentions.

Our research is closely related to the growing literature examining political influence on infrastructure development. Studies have documented how electoral incentives shape infrastructure decisions(Akbulut-Yuksel et al., 2024; Fajgelbaum et al., 2023). Prior literature has also revealed regional favoritism as an alternative politicians' motive behind their decision on infrastructure allocation (Burgess et al., 2015; Alder et al., 2019). Our paper extends the literature by focusing not on the political causes but the sectoral impacts and broader economic consequences, particularly how politically driven inefficiencies in transportation route design affect interregional economic connectivity.

Given our focus on regulations in the airline industry, this paper also contributes to

the literature that investigates the impact of regulation and deregulation in this sector. Following the Airline Deregulation Act of 1978 in the U.S., economists have studied its economic impacts on fares (Moore, 1986), economies of scale (Brueckner and Spiller, 1994), and on local population, income, and employment growth (Blonigen and Cristea, 2015). For international flights, Winston and Yan (2015) analyze the welfare effects of open skies agreements on U.S. international routes. Although airspace regulation is prevalent due to geopolitical conflicts, military regulations, and other political factors, it has received limited attention in the literature.[7] We extend the literature by providing empirical evidence on how airspace regulations shape the airline industry and how the impacts cascade into broader economic outcomes.

The rest of the paper is organized as follows: Section 2 discusses the background of airspace regulation and airline industry in mainland China. Section 3 describes the data utilized in our empirical analysis. Section 4 outlines our empirical strategies, followed by the empirical results presented in Section 5. Finally, Section 6 concludes the paper.

2 Background

2.1 Airspace regulation

Airspace regulation is a common form of regulation in the heavily regulated airline industry after World War II, largely due to political considerations. For instance, before its collapse in 1991, the Soviet Union prohibited Western flights from crossing its airspace, forcing airlines to take extensive detours, driving up costs, and significantly reducing connectivity among Asia, North America, and Europe. As a result, Anchorage became an important hub connecting Asia and North America. Following the Soviet era, Russia opened its skies but introduced fees of around $10000 for commercial flights using its airspace. The Russo-Ukrainian war in 2022 added further complications by prompting many Western countries to avoid Russian airspace altogether, thereby restricting direct routes and increasing operational costs. In the Middle East, several Arab states have periodically barred Israeli aircraft, underscoring how political and security concerns can alter flight paths. Before deregulation in Argentina in 2016, most domestic flights had to stop in the capital, limiting links between other regions.

[7] One exception is Besedeš et al. (2024), who uses Russia's closure of its airspace as a natural experiment to study the impact of distance on trade costs.

Other examples include mainland China not allowing Taipei-based airlines like China Airlines and EVA Air to use its airspace, leading to significant detours for the flights that connect Taipei and Europe.[8]

Mainland China provides a unique opportunity to study airspace regulation, blending a booming aviation market with stringent airspace regulations. Around 80% of the space is controlled by the air force, leading to significant curvature even in the domestic airline routes.[9]

Figure 1 shows the extent of airspace regulation in China and the U.S. Panel (a) presents a screenshot of the real-time flight map in China from Flightradar24, a flight tracking website that monitors almost all commercial flights worldwide. Panel (b) presents a screenshot of the real-time flight map from the U.S. Both screenshots were taken around noon (local time) on January 9, 2025. As shown in these maps, we observe many gaps in the flight map in China, even in the densely populated Central Plains Region and the Eastern and Southern parts of China. Flights also tend to cluster along specific paths in China. In contrast, no such gaps or specific flight paths are observed in the U.S. The gaps in the flight map in China likely indicate that airspaces in these areas are not permitted for commercial flights, suggesting a more stringent level of airspace regulation in China.

Panel (c) of Figure 1 shows the five most curved airline routes in mainland China. The map reveals notable deviations from the shortest paths, indicating that airspace regulations significantly distort airline routes.

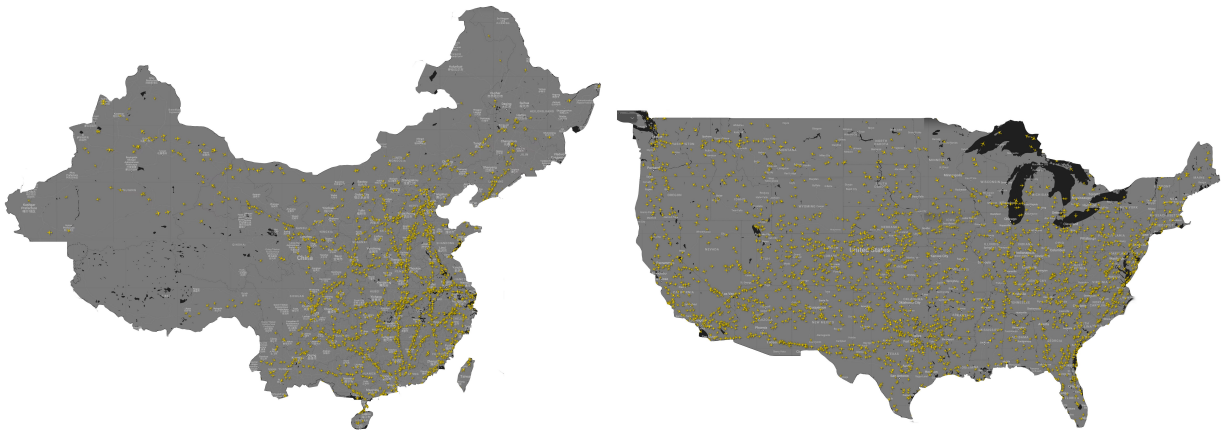
2.2 Airline industry in China

China's airline industry evolved rapidly after the 1990s, along with the countries' market reforms and privatization. Previously, commercial airlines was centrally managed by the Civil Aviation Administration of China (CAAC). However, starting in the mid-1980s and continuing into the early 1990s, airlines backed by local governments and private entities (e.g., Xiamen Airlines and Xinjiang Airlines) were permitted to enter the commercial air transport sector (Wang et al., 2016). In 2005, the CAAC opened civil aviation to private

[8]South China Morning Post "Why the World's Flight Paths are Such a Mess", October 1, 2018, available at https://multimedia.scmp.com/news/world/article/2165980/flight-paths/index.html, retrieved on January 15, 2025.

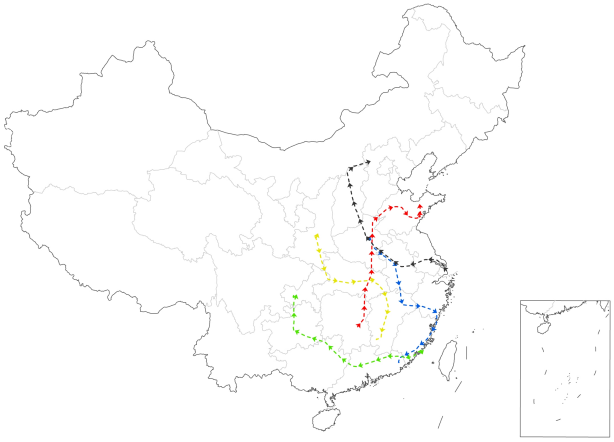
[9]Source: https://finance.sina.cn/china/gncj/2014-07-23/detail-iavxeafr5439198.d.html?from=wap, retrieved on January 15, 2025.

Figure 1: Airspace regulation in China and the U.S.



(a) Real-time flight map in China

(b) Real-time flight map in the U.S.



(c) Five most curved airline routes in China

Notes: Panels (a) and (b) show real-time flight maps from www.flightradar24.com for mainland China and the U.S. (excluding Alaska and Hawaii), at 11:58 AM Beijing time and 12:37 PM EST on January 9, 2025. Panel (c) displays five of China's most curved airline rounts over 1000 km: Shanghai–Zhangjiakou (Curvature: 49.9%, black), Hengyang–Qingdao (Curvature: 44.5%, red), Zhengzhou–Jieyang (Curvature: 43.1%, blue), Xi'an–Ganzhou (Curvature: 43.1%, yellow), and Chongqing–Quanzhou (Curvature: 42.3%, green).

investment, resulting in a rapid proliferation of private airlines, particularly those established to meet demand in expanding local markets. There are a total number of 49 airlines in China in 2019. However, the three biggest airlines–Air China, China Eastern Airlines, and China Southern Airlines– and their subsidiaries account for around two-third of the market share in the domestic market.

In recent years, China's airfare pricing has also shifted toward a more market-oriented model, with the gradual relaxation of fare controls, particularly on high-demand routes. The

CAAC has set a price cap for economy class on most routes based on distance.[10] For around 200 high-demand routes, the government has removed these price caps since 2013. Most of the time, especially during non-national holidays, price caps are not binding.

Airlines must submit a formal application to the CAAC to operate in new routes. The application has to include detailed information regarding the proposed route, aircraft type, flight schedule, and operational plan. If a new route involves using airspace that is not currently designated for commercial use, the airline must obtain approval from the Air Forces of the respective theater commands. If the route spans multiple military regions, the airline needs to secure approval from all involved theater commands. In addition to the approval from the theater commands, the airlines also need to secure support from the local government, and demonstrate they have the necessary operational capacity, including qualified flight crews, ground-handling services, and maintenance support.

The airspace regulations, as well as the airline routes, rarely change over time. This is evidenced by the fact that around 95% of the scheduled airline routes remain exactly the same as they were in 1995.

3 Data and Measures

This section describes the construction of key variables used in this study. Summary statistics of the relevant variables are presented in Table A1.

Airline routes The airline routes are constructed using the flight trajectories from the Flightradar24 (www.flightradar24.com), a global flight tracking service provider. This dataset covers all commercial flights in the mainland China. For each commercial flight, we have the information on its latitude and longitude coordinates, reported every 10 to 30 seconds. This enables us to delineate the airline route for each flight in the geographic information system (GIS) and then calculate the actual flight distance. The curvature of each route is defined as: $Curvature_{i,j} = (\frac{\text{Actual Distance}_{i,j}}{\text{Shortest distance}_{i,j}} - 1) \times 100\%$, where the shortest distance is the great-circle distance between the departure and arrival airports.

[10] The price cap for most non-mountainous airline routes is: $Log(150, 0.6 \cdot Distance) \cdot Distance \cdot 1.1 \cdot 1.25$. Based on this formula, the price cap for a 500km route is around 730CNY (104USD), and the price cap for a 4500km route is around 4500CNY (643USD).

Airfares data We obtained the airfares data from Ctrip (www.ctrip.com), the largest online travel agency in mainland China. This dataset contains the average economy-class price and arrival delay rate for almost all commercial flights scheduled between September 16 and September 22, 2019.[11,12] We aslo calculated the number of flights per week for each airline route based on this dataset. It is worth noting that the flight schedule in China is organized on a weekly basis. Within a flight season, the flight schedules for each week are almost the same, making our one-week data representative.

Population mobility To measure cross-city population mobility, we compiled two sources of data. The first one is the 2019 Weibo mobility index, sourced from the Spatial Data Lab at Harvard University.[13] The Weibo mobility index is constructed by aggregating records of individuals' travel patterns based on the geographical information from users' posts on Weibo, the largest social media platform in China.[14] This data is at the origin-destination city pair level. Each observation in this data represents the travel intensity from the origin city i to the destination city j.

Second, we used the online search index (Baidu Index) in 2019 to measure cross-city migration intentions.[15] Baidu is the world's second largest search engine, trailing Google, whose market share in China is 73% in June 2019.[16] Baidu tags each query with the user's geographic location at the time of the search.[17] We extract search queries that clearly relate to migration intention, such as "moving to city j" or "employment in city j". The online search index is constructed by aggregating these search queries at the origin-destination city pair level. Each observation in this data represents the intensity of the search of the city i' population in terms of migration to or work in the destination city j.

[11]We use the data from this time period since we want to avoid the impact of the COVID-19 shock, and this week also does not overlap with any major national holidays.

[12]We do not include flights that depart from or arrive at airports in autonomous prefectures in our analysis, as there is a lot of missing information in both the airfares and other outcome variables. The GDP in these prefectures account for around 1% of the national total.

[13]Data source: https://dataverse.harvard.edu/dataverse/weibomobilityindex

[14]Weibo had 516 million active users at the end of 2019 (36.6% of China's population).

[15]Data source: https://index.baidu.com

[16]Source: https://marketmechina.com/wp/wp-content/uploads/2019/07/baidu-market-share-search-engines-china-jun-2019.pdf

[17]This index has been used in previous works to study people's divorce decisions (Alm et al., 2022) and sentiment in the stock market(Fang et al., 2020).

Cross-city investment Firms' cross-city investment data is constructed based on the universal firm registration database from the State Administration for Industry and Commerce.[18] For each registered firm, we have access to its geo-coded address and its subsidiaries. In total, we extracted records of 22456 subsidiaries established in 2019. By utilizing the address of the parent company (origin) and the addresses of its subsidiaries in other cities (destination), we can measure cross-city firm investment at the origin-destination city pair level.

Cross-city patent collaboration The cross-city patent collaboration network is constructed using patent records granted in 2019, sourced from the China National Intellectual Property Administration database.[19] After extracting the full set of 2.6 million granted patents, we identified 20318 patents with multiple assignee firms. The firm names from the patent records were then matched with the firm registration record database, allowing us to determine the registered location of each assignee. This geographic information enabled us to identify patents involving collaborations between firms from different cities. Using this data, we constructed a city-pair gravity dataset of cross-city patent collaborations as our fourth measure of economic connectivity.

4 Empirical Strategies

4.1 Empirical specification

To explore the impact of curvature in the airline route on key outcomes, we estimate the following equation:

$$Y_{i,j} = \beta_1 Curvature_{i,j} + \alpha_i + \theta_j + \gamma X_{i,j} + \epsilon_{i,j} \tag{1}$$

where i denotes the departure city, and j denotes the arrival city. $Y_{i,j}$ represents the key outcome variables, including (1) the logarithm of the economy-class airfares; (2) the number of flights per week on a given route i, j; (3) the arrival delay rate; (4) the number of subsidiaries in city j whose parent firms come from city i; (5) indices for Weibo mobility and online search intensity from city i to city j; and (6) the number of patent collaborations

[18] Data source: https://www.gsxt.gov.cn/index.html

[19] Data source: https://search.cnipr.com

between city i and city j.[20]

$Curvature_{i,j}$ is the key independent variable and measures the curvature of the airline route from city i to city j. α_i and θ_j represent the departure city and the arrival city fixed effects, respectively. $X_{i,j}$ comprises a set of control variables, including the logarithm of the shortest (great-circle) distance from city i to city j, the presence of a direct high-speed railway connection between city i and city j in 2019, and whether city i and j are both vice-provincial-level cities. It is worth noting that city-level characteristics are absorbed by α_i and θ_j.

4.2 Identification

One potential concern regarding the reduced-form regression in Equation (1) is the possibility of omitted variable bias. Cities with greater political and economic significance may face higher levels of airspace regulation, as they are more likely to have nearby military bases (e.g., Beijing). This could result in more curved airline routes connecting these cities. Conversely, airlines may have incentives to lobby for straighter routes between major cities due to profit considerations.[21]

We use an instrumental variable (IV) approach to deal with the issue of endogeneity. When designing new airline routes, airlines often rely heavily on existing routes, as obtaining authorization for new airspace is costly. For instance, if cities A and B already share an established route and cities C and D are nearby, the curvature of a new route between C and D will likely mimic that of the A-B route. This "free-riding" strategy effectively allows airlines to minimize the cost of applying for the new airline routes.[22] Following this idea, we construct two IVs using airline route data from 1995, the earliest year for which such data is available. In 1995, 687 city pairs were connected by airlines. Our IVs are designed to predict the curvature of airline routes for 740 city pairs in our sample that were not connected in 1995 but became connected by 2019. Our first IV is constructed in two steps, as illustrated in Appendix Figure B: (1) we use the airline routes from 1995 to predict an

[20]It is worth noting that, for the ticket price regressions, the observations are at the flight level. All other regressions are estimated at the airline route (i, j) level.

[21]It is important to note that, most airline routes have remained the same over time. This prevents us from estimating the baseline equation and addressing the issue of endogeneity through a difference-in-differences approach.

[22]The concept of this IV is similar to the IV used in Faber (2014), where they predict the railway path based on the least-cost path.

airline route connecting two cities that were not connected in 1995; (2) we calculate the predicted curvature by dividing the length of the predicted route by the shortest distance between the two cities. Similarly, our second IV is constructed based on the average curvature of the five closest routes as of 1995.[23]

The exclusion restriction can still be violated if the predicted curvature of airline routes correlates with political and economic characteristics of cities (Faber, 2014). To address this concern, we include departure and arrival city fixed effects.[24] We also control for whether the city pairs have a direct High-Speed Rail (HSR) connection in 2019 to eliminate the potential impact of alternative transportation infrastructure. Additionally, it is worth noting that since we use airline routes established in or before 1995 to construct the two IVs, our IV regressions focus exclusively on city pairs that were unconnected in 1995 but became connected by 2019, rather than on the more significant city pairs that were already connected in 1995. The samples in our IV strategy cover less important city pairs, whose curvatures are less likely to be influenced by the cities' economic and political characteristics.

Furthermore, in Table A3, we examine the relationship between cities' observable characteristics and airline route curvature. The results indicate that neither cities' economic characteristics (GDP and population) nor cities' political status (whether a city is a vice-provincial-level city) affect the airline route curvature.

5 Empirical Results

This section presents the estimation results and robustness checks of Equation (1) for various outcomes. We first focus on the impact of airspace regulations on airfares, flight frequency, and delay rate. We then analyze how these regulatory impacts cascade into broader economic outcomes. Finally, using the predicted route curvature from our IV strategy, we investigate the impact of airspace regulation on aero-connectivity.

To enhance the interpretability of the results, we normalize the main independent variable, $Curvature_{i,j}$, to have a mean of 0 and a standard deviation of 1. A 1.2-standard-

[23]The results remain robust when we use the number ranging from 1 to 10.

[24]It is worth noting that, thanks to our data structure, our controls are more comprehensive than those used in Faber (2014), which account for province fixed effects, and counties' economic and political characteristics—such as agricultural and urban populations, whether the county has township status, and whether the county seat is a prefectural capital.

deviation decrease in airline route curvature can bring mainland China's airline route curvature to the U.S. level.

5.1 The impact of airspace regulations on airfares, flight frequency, and delay rate

Table 1 summarizes how route curvature affects airfares, flight frequency, and flight arrival delay rate. Column (1) presents the OLS results, controlling for departure and arrival city fixed effects, and the logarithm of the shortest distance between the airport in city i and the airport in city j. Column (2) adds additional controls, including whether $Route_{i,j}$ has a direct HSR connection and whether city i and city j are both vice-provincial level cities. Column (3) shows the OLS results with all controls included, using the same sample as in the IV estimation. Columns (4) and (5) display the IV estimation results. It is worth noting that, since we use airlines established before 1995 to construct the IVs for $Curvature_{i,j}$ for airlines established after 1995, we do not include airlines established in 1995 in our IV estimation. Consequently, the number of observations in Columns (4) and (5) is smaller than in Columns (1) and (2). The first-stage results of the IV estimation are reported in Appendix Table A2.

Panel A of Table 1 reports the impact of airline route curvature on the logarithm of airfares. The observations are at the *flight* level. We find that both OLS and IV regression results suggest that airline route curvature significantly increases airfares, with the IV estimates being larger than the OLS estimates. The point estimate in Column (5) indicates that if China were to relax airspace regulations by one standard deviation, the average airline ticket price could decrease by approximately 5%.

If we assume that variable costs (e.g., fuel costs, depreciation costs, maintenance costs, and crew costs) linearly correlate with mileage and account for 75% of the total cost (Koopmans and Lieshout, 2016), a back-of-the-envelope calculation suggests that approximately 67% of the cost increase due to the curved airline route is passed through to consumers, based on the IV estimates from Column (5).[25]

We then turn our attention to the impact of airspace regulation on flight frequency. The results are reported in Panel B, Table 1. The observations for this regression are at the

[25] $\frac{0.05}{0.75 \cdot 0.1} = 0.67$, where 0.1 represents a one-standard-deviation change in route curvature.

Table 1: Impact of route curvature on airefares, flight frequency, and competition

Estimation method	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Panel A: Dep. Variable: Log average price of flights					
Curvature$_{i,j}$	0.0225***	0.0203***	0.0175*	0.0535***	0.0506***
	(0.00728)	(0.00726)	(0.00904)	(0.0186)	(0.0187)
Sample mean	4.56	4.56	4.54	4.54	4.54
Observations	69694	69694	21239	21239	21239
Adjusted R^2	0.620	0.622	0.642		
KPF statistics				29.7	29.7
Panel B: Dep. Variable: Number of flights per week					
Curvature$_{i,j}$	-2.111***	-1.852***	-0.980	-3.845**	-3.228**
	(0.661)	(0.642)	(0.700)	(1.804)	(1.585)
Sample mean	24.77	24.77	14.50	14.50	14.50
Observations	2807	2807	1452	1452	1452
Adjusted R^2	0.482	0.539	0.553		
KPF statistics				39.5	39.5
Panel C: Dep. Variable: Flight arrival delay rate (%)					
Curvature$_{i,j}$	-0.0989	-0.0772	0.0212	2.446***	2.558***
	(0.179)	(0.181)	(0.344)	(0.921)	(0.944)
Sample mean	13.31	13.31	15.89	15.89	15.89
Observations	69694	69694	21239	21239	21239
Adjusted R^2	0.191	0.191	0.253		
KPF statistics				29.7	29.7
Controls	Basic	Full	Full	Basic	Full
Departure city FE	Yes	Yes	Yes	Yes	Yes
Arrival city FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β_1 from the variants of Equation (1). Panel A uses the logarithm of the average price of flights on the route as the dependent variable, Panel B uses the number of flights, and Panel C uses the flight delay rate (%). Columns 1-3 report OLS results, and columns 4 & 5 reports IV results. The first stage of IV estimations are reported in Table A2. Column 1 includes the basic control variable, the logarithm of the shortest (great-circle) distance between departure and arrival city. Column 2 adds extra controls, including a dummy of high speed railway connection and an indicator of the city pair political hiararchy. Column 3 restricts sample as in columns 4 & 5 which replicate columns 1 & 2 with IV estimations. All regressions include further includes departure city and arrival city fixed effects. Robust standard errors clustered at the city-pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

airline-route level. We find that a one-standard-deviation increase in the curvature of an airline route significantly reduces the number of flights on $Route_{i,j}$ by 3.2 flights per week (or 22% of the sample mean). The reduction in flight frequency can be attributed to a decrease in demand due to higher prices and a decrease in supply caused by increased costs.

In Panel C of Table 1, we explore how curvature affects the flight delay rate. The results provide some suggestive evidence that increased airline route curvature is also associated with higher flight delay rates. This may be due to a greater concentration of air force activities in the airspace over more curved routes.

Overall, the results in Table 1 indicate that curved airline routes in China adversely affect the Chinese airline industry. These routes significantly increase carriers' operational costs, elevate consumer prices, and reduce carriers' profit margins. A back-of-envelope calculation suggests that if mainland China can reduce the airline route curvature to the U.S. level (by 1.2 standard deviation), the airfares will be 6% lower, there will be 3.9 more flights on a given route per week, and the delay rate will be increased by 3 percent points.

5.2 Broader economic outcomes

In this subsection, we explore whether increased airfares, reduced flight frequencies, and competition cascade into broader economic outcomes, affecting economic connections between cities. The specification in each column remains the same as in Table 1. Observations in all regressions are at the city-pair level.

Panel A of Table 2 examines how route curvature influences firms' cross-city investment. The results indicate that a one-standard-deviation increase in route curvature between city i and city j reduces the number of subsidiaries established in city j by firms from city i by approximately 1.3, which represents about 12% of the sample mean. One interpretation of the result is that curved airline routes may increase the cost of personal communication and interaction between cities, thereby raising information acquisition costs and reducing information exchange.

We also find some negative effects of airline route curvature on patent collaborations across cities, as shown in Panel B of Table 2, though the coefficients are estimated with less precision compared to those in Panel A. Similar to firm investment, patent collaboration heavily depends on interpersonal interaction, which is hindered by curved airline routes through higher airfares, lower flight frequency, and higher flight delay rates.

To formally test the impact of curved airline routes on interpersonal connections and mobility across cities, we use online search intensity related to employment or migration from city i to city j (Baidu Index) and social media users' mobility data based on the location of their posts (Weibo mobility index) as outcome variables. The results are presented in Panels C and D of Table 2, respectively. The findings in both panels confirm that airspace regulations significantly reduce individual mobility and information exchange between cities.

Table 2: Broader economic impact of route curvature

Estimation method	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Panel A. Firm cross-city investment (Dep. Variable: # of subsidiaries)					
$\text{Curvature}_{i,j}$	-0.657***	-0.505**	-0.615**	-1.552**	-1.337**
	(0.251)	(0.246)	(0.294)	(0.608)	(0.609)
Sample mean	16.07	16.07	10.49	10.49	10.49
Adjusted R^2	0.737	0.751	0.720		
Panel B. Research collaboration (Dep. Variable: # of collaborated patents)					
$\text{Curvature}_{i,j}$	-0.380*	-0.281	-0.287	-1.152*	-0.997*
	(0.218)	(0.212)	(0.260)	(0.602)	(0.594)
Sample mean	7.22	7.22	4.32	4.32	4.32
Adjusted R^2	0.570	0.585	0.566		
Panel C. Migration intension (Dep. Variable: Online search index)					
$\text{Curvature}_{i,j}$	-0.0934*	-0.0723	-0.134***	-0.348***	-0.299***
	(0.0547)	(0.0474)	(0.0457)	(0.117)	(0.0984)
Sample mean	7.33	7.33	5.98	5.98	5.98
Adjusted R^2	0.849	0.878	0.890		
Panel D. Population mobility (Dep. Variable: Mobility index)					
$\text{Curvature}_{i,j}$	-0.0780	-0.0605	-0.142	-0.577**	-0.497***
	(0.125)	(0.109)	(0.114)	(0.233)	(0.189)
Sample mean	2.49	2.49	1.38	1.38	1.38
Adjusted R^2	0.553	0.645	0.705		
Observations	2807	2807	2035	2035	2035
KPF statistics				39.5	39.5
Controls	Basic	Full	Full	Basic	Full
Departure city FE	Yes	Yes	Yes	Yes	Yes
Arrival city FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β_1 from the variants of Equation (1). Panel A uses the number of subdidiaries as the dependent variable, Panel B uses the number of collaborated patents, Panel C uses online search index, and Panel D uses Weibo mobility index. Columns 1-3 report OLS results, and columns 4 & 5 reports IV results. The first stage of IV estimations are reported in Table A2. Column 1 includes the basic control variable, the logarithm of the shortest (great-circle) distance between departure and arrival city. Column 2 adds extra controls, including a dummy of high speed railway connection and an indicator of the city pair political hiararchy. Column 3 restricts sample as in columns 4 & 5 which replicate columns 1 & 2 with IV estimations. All regressions include further includes departure city and arrival city fixed effects. Robust standard errors clustered at the city-pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.3 Aero-connectivity

The results reported in Sections 5.1 and 5.2 focus on established airlines. Another critical effect of airspace regulations is that they can deter the establishment of new airline routes, which may further impact cities' economic connections. In this section, we investigate how route curvature affects aero-connectivity between cities, specifically concerning the existence of non-stop flights connecting two cities.

Based on the results of the IV estimation (reported in Appendix Table A2), we predict the curvatures of routes that were not yet introduced during our 2019 sample period. We then estimate the following reduced-form equation to explore the impact of potential airline route curvature on aero-connectivity:

$$Y_{i,j} = \beta_1 PredictedCurvature_{i,j} + \alpha_i + \theta_j + \gamma X_{i,j} + \epsilon_{i,j} \quad (2)$$

where the dependent variable, $Y_{i,j}$, is a dummy variable indicating whether city i and city j are connected by a non-stop flight in 2019. The terms α_i and θ_j represent the departure and arrival city fixed effects, respectively. $X_{i,j}$ is a set of city-pair characteristics, as previously defined.

Table 3: Impact of predicted route curvature on connectivity

Estimation method	Reduced form of the IV strategy	
Dependent variable	Dummy of air connection	
	(1)	(2)
Predicted Curvature$_{i,j}$	-0.0235***	-0.0256***
	(0.00560)	(0.00562)
Sample mean	0.256	0.256
Observations	13370	13370
Adjusted R^2	0.305	0.305
Controls	Basic	Full
Departure city FE	Yes	Yes
Arrival city FE	Yes	Yes

Notes: This table reports estimates of β_1 from the variants of Equation (2). Column 1 includes the basic control variable, the logarithm of the shortest (great-circle) distance between departure and arrival city. Column 2 adds extra controls, including a dummy of high speed railway connection and an indicator of the city pair political hiararchy. All regressions include further includes departure city and arrival city fixed effects. Robust standard errors clustered at the city-pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

The results reported in Table 3 suggest that the underlying curvature of airline routes has a significant negative impact on aero-connectivity. Specifically, if the underlying curvature between cities i and j increases by one standard deviation, the probability of these two cities being connected by a direct flight decreases by 2.3 percentage points (or 9% of the sample mean).

6 Conclusion

This paper uses China's restrictive commercial airspace as a case study to investigate the economic impacts of inefficiencies in transportation networks. Different from the existing

literature that primarily focuses on the economic impacts of whether transportation infrastructure is connected, this paper studies the "quality" of the connection. Airline industry provides an ideal setting for our study. Unlike land transportation, where optimal routes are shaped by multiple physical barriers such as mountains and rivers, air travel can be benchmarked against the great circle distance—the shortest path between two points on a sphere.

We collected a novel dataset containing information about flight trajectories to measure actual flight distances and calculate airline route curvatures. We used the historical route data to construct instrumental variables and controlled for both the arrival and departure city fixed effects to address endogeneity concerns. Our analysis reveals that, due to the restrictive use of commercial airspace, the average route curvature in China is 17%, significantly higher than the 5% average in the U.S. and Europe. Both OLS and IV strategies indicate that significant airline route curvature increases airfares, reduces flight frequency, and decreases the number of aero-connected city-pairs. These inefficiencies generate substantive economic costs, hindering intercity activities such as personal travel, population migration, cross-city corporate investment, and patent collaboration.

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Appendix

A Further data description

Table A1: Descriptive Statistics

Variable	Obs	Mean	SD	10^{th} pct	Median	90^{th} pct
Panel A. Airline routes						
Curvature (%)	2807	17.2	9.6	7.2	15.2	28.9
Shortest (great-circle) distance (km)	2807	1186.3	498.1	620.7	1127.9	1814.4
Panel B. Flight data						
Average price of flights (USD 2019)	69694	104.7	48.1	54.8	94.1	170.6
Flight delay rate (%)	69694	13.3	14.4	0	8.7	33
# of flights	2807	24.8	32.2	4	14	60
Herfindahl-Hirschman Index (HHI)	2807	.7	.3	.3	.6	1
Panel C. City-pair data						
Weibo Mobility Index	2807	2.5	4.9	.1	.8	5.7
Baidu Search Index	2807	7.3	4.7	3.3	5.9	13.2
# of branch firms	2807	16	16.3	1	8	47
# of collaborated patents	2807	7.2	11.1	0	1	32
Dummy of high speed railway connection	2807	.5	.5	0	0	1
City pair political hiararchy	2807	.1	.3	0	0	1
Dummy of air connection	14626	.3	.4	0	0	1

Notes: This table summarizes the descriptive statistics of relevant variables used in our empirical analyses.

B IV construction

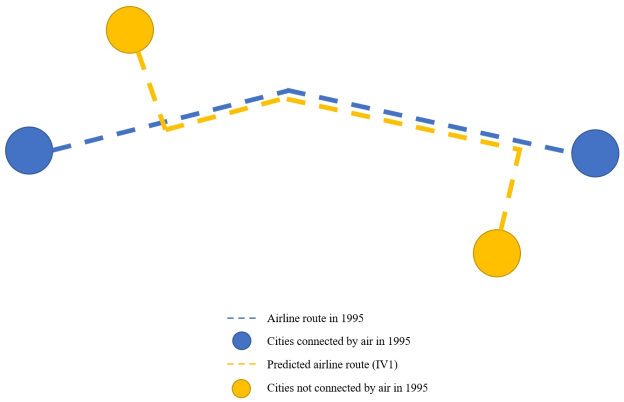


Figure A1: Illustration of the construction of the curvature IV1

Notes: Our first IV is constructed in two steps: (1) we use the airline routes from 1995 (blue dashed line) to predict the airline route connecting two cities that were not connected in 1995 (orange dashed line); (2) we calculate the predicted curvature (IV1) by dividing the length of the predicted route (orange dashed line) by the shortest distance between two cities that were not connected in 1995.

C First stage of IV estimations

Table A2: First stage of IV estimations

Estimation method	OLS			
Dependent variable	Curvature (%)			
	(1)	(2)	(3)	(4)
$IV1_{i,j}$	3.840***	3.768***	4.396***	4.389***
	(0.954)	(0.945)	(0.771)	(0.771)
$IV2_{i,j}$	9.497***	9.448***	7.927***	7.785***
	(1.490)	(1.501)	(1.365)	(1.368)
Observations	21239	21239	1452	1452
Adjusted R^2	0.218	0.219	0.047	0.048
Controls	Basic	Full	Basic	Full
Departure city FE	Yes	Yes	Yes	Yes
Arrival city FE	Yes	Yes	Yes	Yes

Notes: This table reports the first stage results of IV estimations in columns 4 & 5 of Table 1. IVs applies to routes that were connected after 1995. $IV1_{i,j}$ is the predicted the shortest route connecting two cities, using the airline routes from 1995. $IV2_{i,j}$ is the average curvature of the five closest routes as of 1995. Robust standard errors clustered at the city-pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

D Airline route curvature and city characteristics

Table A3: Relationship between airline route curvature and city characteristics

Estimation method	OLS	
Dependent variable	Curvature (%)	
	(1)	(2)
Population (departure city)	0.00109	0.00182
	(0.00607)	(0.00607)
GDP (departure city)	0.0242	-0.00772
	(0.0585)	(0.0638)
Population (arrival city)	0.000761	0.00147
	(0.00606)	(0.00606)
GDP (arrival city)	0.0274	-0.00316
	(0.0587)	(0.0640)
Political hiararchy (departure city)		0.0586
		(0.0506)
Political hiararchy (arrival city)		0.0564
		(0.0506)
Log shortest distance	-0.914***	-0.918***
	(0.0766)	(0.0765)
Observations	2822	2822
Adjusted R^2	0.149	0.150

Notes: This table reports the relationship between airline route curvature and city characteristics. The populations of the departure and arrival cities are measured in millions. The GDP statistics of the departure and arrival cities are measured in trillions of CNY. Political hiararchy variable is a dummy that equals 1 if the departature/arrival city is the vice-provincial-level city. Robust standard errors clustered at the city-pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.