# Air Connectivity and International Travel: Evidence from Cross-border Card Payments*

Chun-Yu Ho† Tingting Peng‡ Haruka Takayama§ Li Xu¶

February 24, 2024

**Abstract**

Many countries seek to attract foreign travelers. How do direct flight connections affect the spending of international visitors? A novel dataset on card payments made by Chinese travelers through point-of-sale (POS) terminals enables us to investigate that question. We instrument for the frequency of direct flights between Chinese cities and foreign countries by exploiting overseas airport expansions as exogenous shocks. Our IV estimates indicate that a 1% increase in the weekly frequency of direct flights leads to a 2% increase in cross-border card transaction value. This suggests that in a city with the average frequency, adding one extra weekly direct flight increases the value of transactions by 52% to the destination country. While improving air connectivity promotes international travel, we find that negative shocks to consumer preferences for destination countries, such as boycotts, diminish the positive impact of air connectivity.

Keywords: International Travel, Bilateral Trade, Air Transportation, and Trade Cost
JEL Classification: F10, F14, L93

*We thank Costas Arkolakis, Maggie Chen, Kerem Coşar, Anca Cristea, Peter Egger, Brett Fischer, Simon Fuchs, Inga Heiland, Ebehi Iyoha, Hayato Kato, Veronica Rappoport, Kim Ruhl, Georg Schaur, Bengt Söderlund, Yoichi Sugita, Tom Zylkin, and seminar/conference participants at Keio University, Kyushu University, the Midwest Trade conference, the Southern Economic Association, the Asian Meeting of the Econometric Society, the China Economics Annual conference, and the Chinese Economists Society, for comments and suggestions. All errors are our own.

†Department of Economics, University at Albany, State University of New York, cho@albany.edu
‡Department of Economics, University at Albany, State University of New York, tpeng2@albany.edu
§Department of Economics, University at Albany, State University of New York, htakayama@albany.edu
¶Antai College of Economics and Management, Shanghai Jiao Tong University, shirleyxu@sjtu.edu.cn

# 1 Introduction

International tourism has steadily grown for over six decades, contributing, on average, 4.4% to the GDP of OECD countries (OECD 2020).[1] For example, international tourism ranks as the world's third-largest export category, following fuels and chemicals, and surpassing automotive products and food (UNWTO 2021). International visitors spend on services and goods in their destination countries, which generates demand and creates jobs in tourism-related industries, such as food and beverage services, shopping, and traveler accommodations (BEA 2023). Given its importance, policymakers are actively engaged in policies to increase inbound arrivals, including investments in air transportation infrastructure and the expansion of air connectivity. However, there is limited evidence on how the development of air transportation promotes international travel, which hinders the evaluation of related policy initiatives. This paper addresses this gap and presents the first attempt to examine the effect of air connectivity on the spending of international visitors.

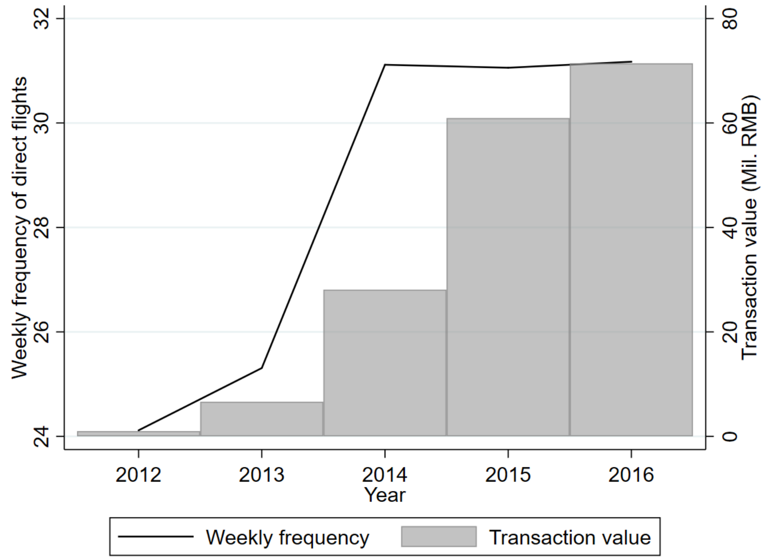
China has made the largest amount of spending on international travel, accounting for one-fifth of global travel spending, followed by the US (UNWTO 2021). Our unique dataset contains Chinese consumer card transactions made in foreign countries, through point-of-sale (POS) terminals. In particular, we observe how much is spent by consumers from a given Chinese city (hereafter, origin city) in a given foreign country (hereafter, destination country). Notably, our dataset provides the amount of spending by Chinese travelers—a crucial factor for analyzing the economic impact of international travel—rather than the number of travelers. We combine these transaction data with global flight schedules between Chinese cities and foreign countries, which allows us to measure air connectivity between two locations. We construct a yearly origin city-destination country panel spanning 2011-16 and measure the air connectivity using the weekly frequency of direct flights.

Our data present a clear picture of how direct flight connections relate to the spending of Chinese travelers. Figure 1 shows the total number of weekly frequency of direct flights and the total value of card transactions from China to Qatar.[2] In Qatar, Hamad International

[1]For example, trade in travel services, such as tourism and business trips, accounts for a quarter of overall services trade, significantly contributing to the global economy.

[2]We focus on the Chinese cities connected with Qatar via direct flights. Prior to 2013, there were direct flight routes from Doha to Beijing, Chongqing, Guangzhou, and Shanghai. In 2013, Qatar Airways started

Figure 1: Transaction Values and the Number of Direct Flights Between China and Qatar




Notes: We focus on the Chinese cities with direct flights to Qatar from 2012 to 2016. The value of transactions is in millions RMB. We omit 2011 because no transaction value is recorded in the data.

Airport started operations in April 2014, which has 12 times bigger capacity than the old airport and would be able to accommodate 53 million passengers every year after all expansions.[3] Because of the new airport opening, Qatar Airways began new direct flight routes from Doha to Chengdu and Hangzhou in September and December 2013, respectively. These events added seven weekly direct flights from China to Qatar in 2013, and we observe that the spending of Chinese travelers in Qatar has increased as well.

Is the investment in the new airport worth it for Qatar's economy? The new direct flights in China account for 1% of the total increase in international flights arriving in Qatar after the airport opening. The total amount of investment is 15.5 billion USD. If we consider the new airport will benefit Qatar's economy for sixty years, we estimate the cost to increase the frequency of direct flights in China as $(15,500/60) \times 0.01 = 2.58$ million USD per year.[4] In contrast, the spending of Chinese travelers from Chengdu and Hangzhou increased by one million USD between 2013 and 2014. Given that this new airport opening contributes to the economy in multiple ways, this fact suggests that an increase in foreign visitor spending can

operating three- and four-weekly flights from Chengdu and Hangzhou to Doha, respectively.

[3]Source for the information (link; accessed on February 10, 2023).

[4]For example, the UK government considers the new Heathrow Northwest runway will benefit passengers and the wider economy over 60 years (link; accessed on February 10, 2023).

be one of the key factors policymakers focus on when considering the benefits of promoting air connectivity.

To analyze the causal relationship between air connectivity and Chinese travelers' spending, we develop a model to explain the bilateral flow of card transactions, following Head et al. (2008) and Farber and Gaubert (2019). Our model accounts for consumer decision-making when choosing among various travel destinations, with the attractiveness of foreign destinations and travel costs (i.e., air connectivity). We derive a gravity equation from the model, which enables us to identify the effect of air connectivity on international travel with three-way fixed effects (FEs): Chinese city-foreign country, Chinese city-year, and foreign country-year FEs.

A potential threat to identification is the reverse causality from cross-border travel to air connectivity: when demand for travel from a Chinese city to a particular country increases, airlines are more likely to connect to that city-country pair with a direct flight. To address this concern, we instrument for air connectivity using overseas airport expansions as exogenous shocks. The motivation for our identifying assumption is that investment in air flight capacity made by foreign governments is uncorrelated with demand shocks for Chinese travelers to that country. In particular, our instrument is the global share of total flights departing from a destination country (representing that country's comparative advantage in air transportation) combined with the geographic distance between a Chinese city and a foreign country (distant locations are less connected by flights; Cristea 2023). The interaction of the two terms represents the differential impact of an overseas airport expansion on travelers in proximate and distant cities.

In our specification, the three-way FEs allow variation only across destination countries, Chinese cities, and years. For example, country-year FEs account for time-varying destination characteristics, including the possibility that airport expansions can enhance countries' attractiveness as travel destinations.[5] We also show that although more flights arrive in countries with airport expansions, the shares of flights from China to those countries are stable over our data period. This supports our identification assumption: the goal of expanding

[5]Additionally, origin-destination FEs ensure that distance (part of our IV) affects our dependent variable (card transaction values) only through air connectivity.

air transportation capacity is to attract more travelers from all over the world, rather than focusing on travelers from China.

Our IV estimate indicates that a 1% increase in the weekly frequency of direct flights leads to a 1.97% increase in the value of card transactions to the destination country. This suggests that if a city with the average frequency of direct flights receives one additional direct flight per week, travelers make 52.45% more card payments in that destination country. We observe a similar estimate using travel time as an alternative measure of air connectivity. Our study contributes to policy formulation, especially when analyzing the impact of the developments in air transportation infrastructures on travelers spending. We use the new Istanbul Airport opening in Turkey as an example and show that the size of expected visitors' spending is fairly large compared to the cost of investment.

Improvements in air connectivity not only affect travelers' spending (i.e., imports of tourism-related services and goods through travel) but also influence trade in goods, particularly imports of consumer products. For instance, passenger planes transport air freight, and consumers who experience new products abroad may develop a preference for those items, leading to more imports. Based on this premise, we conduct further analysis using customs data to study how improvements in air connectivity affect Chinese imports. We find that a higher frequency of weekly direct flights increases the value of imported consumer products that are typically transported by air, such as food and pharmaceuticals.

Our model shows that the attractiveness of travel destinations is one of the important factors in consumers' travel decisions. Such destination characteristic is unique for travel, but not for trade in goods. To explore this model implication, we examine how consumer tastes and preferences toward foreign countries affect our findings by exploiting political conflicts as exogenous adverse shocks. We find that negative sentiment towards foreign countries diminishes the positive effect of air connectivity on cross-border travel—that is, fewer Chinese consumers take advantage of direct air connections when public sentiment shifts against destination countries. However, for goods imports, political conflicts do not affect the impact of air connectivity. This suggests that the impact of air connectivity on international travel is influenced by consumer preferences towards specific destinations, while trade in goods may not be as sensitive to such sentiments.

This paper relates to the literature that studies the effects of international air transportation on economic development (Hovhannisyan and Keller 2015; Campante and Yanagizawa-Drott 2017; Cristea 2023), international trade (Cristea 2011; Alderighi and Gaggero 2017; Wang et al. 2023; Söderlund 2023), foreign investment (Campante and Yanagizawa-Drott 2017; Fageda 2017; Tanaka 2019), and cross-border mergers and acquisitions (Zhang et al. 2021). While attracting foreign travelers is one of the key economic policies, there is no study examining how the development of air transportation networks affects the flow of traveler spending. Our work extends the literature by analyzing the impact of international air transportation on travel, and shows how this effect differs from trade in goods.

Further, we contribute to the literature by introducing a novel identification strategy to estimate the causal impact of air connectivity on economic outcomes. Specifically, we exploit overseas airport expansions as exogenous shocks to enhance air connectivity between Chinese cities and foreign countries. Our motivation for this identification strategy is similar to Cristea (2023) who relies on the proximity of a US city to the domestic aviation network as an exogenous variation in its air connectivity. If a city is closer to the air transportation hub, that city is more likely to be connected by flights. Unlike Cristea (2023), our study focuses on the bilateral flow of direct flights and traveler spending, which makes our identification strategy more plausible. The improvements in air transportation infrastructure are more prevalent globally, and the policy decisions made by foreign governments regarding air transportation developments are less likely to be correlated with the demands of Chinese travelers. Similar to our IV strategy, Söderlund (2023) relies on the liberalization of the Soviet airspace in 1985 as an exogenous variation in travel time and examines its impacts on international business travel.

Our paper is also related to the literature on cross-border travel. Prior studies focus on the consumer demand for cross-border shopping between Sweden and Denmark for specific products, such as alcohol (Asplund et al. 2007) and groceries (Friberg et al. 2022). Additionally, Chandra et al. (2014) and Baggs et al. (2018) examine the response of travelers to exchange rates concerning cross-border travel between Canada and the US.[6] These papers

[6]For example, Chandra et al. (2014) find that a stronger Canadian dollar against US dollar (i.e., a lower foreign price for Canadians) motivates cross-border travel, and the response of cross-border travel to currency fluctuations is mitigated by distance to the border. Baggs et al. (2018) find similar results as Chandra et

focus on countries that are proximate to each other and investigate the effects of price differential and travel costs (proxied by distance) on cross-border travel. In contrast, we study foreign travel between non-contiguous countries, which has been becoming more common as air transportation becomes more affordable. Our setting also includes a large set of destination countries, allowing us to study how consumer sentiment toward a destination affects international travel.

Lastly, our study contributes to a growing body of literature on the impacts of tourism on local economic development. For example, Faber and Gaubert (2018) employ Mexican micro-level data with a spatial equilibrium model and show that tourism leads to local economic gains through its positive spillovers on manufacturing. Additionally, Allen et al. (2023) use the data of card transactions made in Barcelona together with payroll information. Their study suggests that tourism imposes a larger welfare loss on residents in the city center because they face a higher price despite earning a higher wage than peripheral residents. In this strand of literature, Nocito et al. (2023) is the most related to our study. The authors consider the different timings of international releases of a TV series set filming in Sicily, Italy, as positive shocks to local tourism. Unlike those papers, we focus on airport expansions as exogenous shocks and examine the impacts of direct flight connections on traveler spending in foreign countries.

The outline of the paper is as follows. We introduce data and stylized facts in Section 2 and present the model and the empirical strategy in Section 3. We report the main results with cross-border card transaction data in Section 4. Section 5 shows further analysis using customs data. Section 6 concludes.

# 2 Data and Stylized Facts

We use a unique dataset of cross-border card transactions made by Chinese travelers. We merge the card transaction data with international flight schedules to examine the impact of air connectivity on Chinese overseas travel spending. Our novel data show that China has experienced the evolution of air transport networks, which is positively correlated with the

al. (2014) but also show how the cross-border shopping of Canadians to the US hurts Canadian retailers.

value of card transactions.

## 2.1 Data Sources

### (i) Chinese overseas card transactions

A unique dataset of Chinese on-site card transactions enables us to analyze the spending by Chinese travelers overseas. We collect a dataset on card transactions between 2011 and 2016 from a Chinese consumer card provider.[7] The data include transactions made by Chinese cardholders outside China through POS terminals, excluding online transactions. Our data contain the transactions made with cards issued by domestic card brands, excluding foreign brands such as Visa and MasterCard. This limitation does not bias our analysis as the vast majority of Chinese residents use cards issued by Chinese brands (e.g., 99% of the total card payments in China).[8]

We observe the value of transactions by cardholders' cities of residence and countries where the transactions were made.[9] For confidentiality reasons, our data provider aggregates the data at the city of residence-destination country-year level. Although we cannot observe detailed categories for the transactions, this dataset is still informative as it represents the amount of money spent by Chinese consumers who traveled from a particular city to a particular country each year from 2011 to 2016. In our dataset, there are 336 Chinese cities. Our data also include 71 destination countries in Europe and Asia that contribute to 64% of the global exports in trade in travel services (excluding export from China).[10] The destination countries are listed in Appendix Table A.1.

### (ii) Global flight schedules

Our air connectivity data comes from OAG Analyser, which provides worldwide flight sched-

[7] Unfortunately, we only have data available until August 2016 due to a regulation change. We impute the value of transactions for the remaining period (i.e., from September to December 2016) using the monthly transaction data in 2015. This allows us to consider the seasonality of travel demands in different regions. See Appendix B for the details.

[8] Reference: *Global Payments Report 2023*, page 48 (link; accessed on January 21, 2023).

[9] The data provider imputes cities of residence using past card transactions, assuming that a cardholder lives in the city with the highest number of transactions. We also exclude transactions made by Chinese travelers who live outside China (those who made the highest number of transactions in foreign countries).

[10] We calculate the global share of exports in trade in travel services using the WTO trade in services annual dataset.

ules. This dataset includes the name of the departure and arrival airports, departure and arrival time, elapsed time, travel distance, and the number of stops, covering the period from 2011 to 2016. We add the names of Chinese cities served by airports, and latitudes and longitudes of destination countries and Chinese cities. Our primary measure of air connectivity is the weekly frequency of direct flights between a Chinese city and a foreign country.

We also calculate the travel time from a Chinese city to a destination country as an alternative measure. Unlike the weekly frequency of direct flights, we consider indirect flight routes to measure the travel time. Specifically, we first construct all possible flight routes with up to two stops at domestic airports and one stop at a foreign airport. We then add a three-hour layover time for every stop to the total flight duration. Lastly, we select the route with the shortest travel time among all possible flight routes. Additional procedures to measure travel time are outlined in Appendix B.

**(iii) Chinese import data**

Chinese import data are collected by the General Administration of Customs of the People's Republic of China (GACC) for the period of 2011-2016. For each import transaction, we observe the company name, city of the company's location, product name, HS 8-digit product code, country of origin, date (year and month), and transaction value.[11] We classify the imported products into consumer and non-consumer goods using the classification provided by the UNCTAD.[12]

## 2.2 Descriptive Statistics

We merge the two main datasets, the Chinese card transaction data and the flight data. There are 9,859 origin-destination pairs in the final dataset, including 193 unique Chinese cities (origins) and 71 unique foreign countries (destinations).[13] Our data contain the Chinese

[11] We do not have information on the firm location (city) for the year 2016. We identify the company location using a concordance table (link). For the transaction value, we treat the missing observations as zero.

[12] We refer to the classification named "UNCTAD-SoP3: Consumer goods" (link). We classify the industry at the one-digit level of the SITC Revision 4.

[13] We focus on the cities at the prefecture level in mainland China. There are 336 Chinese cities in the card transaction data, but the cities without airports (during our sample period) have not been matched with the flight data.

Table 1: Summary Statistics

| Variables | Mean | P(50) | Min | Max | SD | Observations |
|---|---|---|---|---|---|---|
| *Card transactions* | | | | | | |
| Value (millions RMB) | 10.29 | 0.04 | 0 | 11,263.53 | 114.43 | 59,154 |
| *Flight schedules* | | | | | | |
| Weekly frequency of direct flights | 0.45 | 0 | 0 | 473.56 | 5.71 | 59,154 |
| Travel time (hours) | 13.39 | 14.12 | 0.83 | 25.22 | 4.58 | 46,554 |
| *Imports* | | | | | | |
| Value (millions RMB) | 91.92 | 0.0004 | 0 | 42071.60 | 885.42 | 59,154 |

Notes: We report the mean, the median, the minimum and the maximum values, the standard deviations, and the number of observations for variables we use in regressions. The number of observations for travel time is smaller than for other variables because we cannot construct any flight routes for some city-country pairs, even with three stops.

cities with airports and positive transaction values for at least a year over our data period.

Table 1 presents the descriptive statistics of our estimation sample. The average spending by Chinese travelers is 10.29 million Renminbi (RMB), and the distribution is skewed to the right due to a higher proportion of travelers originating from larger cities. Similar to the transaction value, the distribution of the weekly frequency is also right-skewed because some cities have larger airports that attract more direct flights. On average, there are 0.45 direct flights per week, with a travel time of 13.39 hours. The number of observations for travel time is smaller than for other variables because there is no flight route available for some city-country pairs with three stops.

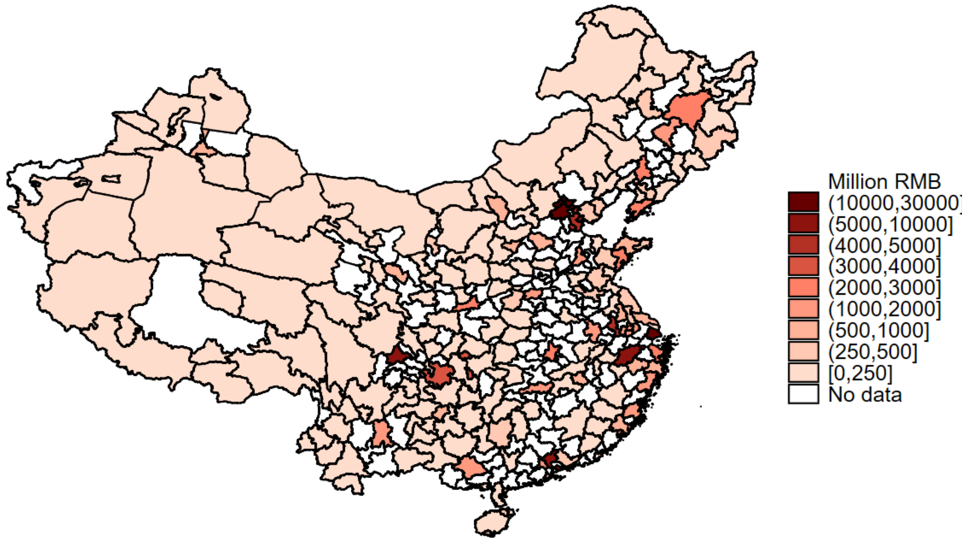
## 2.3 Stylized Facts

We present the three stylized facts that motivate us to investigate the effect of international direct flights on overseas travel spending by Chinese consumers.

**Fact 1: Regional differences in transaction value**

First, we focus on the card transaction data and analyze the increase in the value of transactions between 2011 and 2016. Figure 2 shows the change in the total value of transactions on a map of mainland China from 2011 to 2016, highlighting the variation across origin cities. We observe an increase in the value of transactions in all Chinese cities in our sample,

Figure 2: Change in Card Transaction Values from 2011 to 2016 in Mainland Chinese Cities



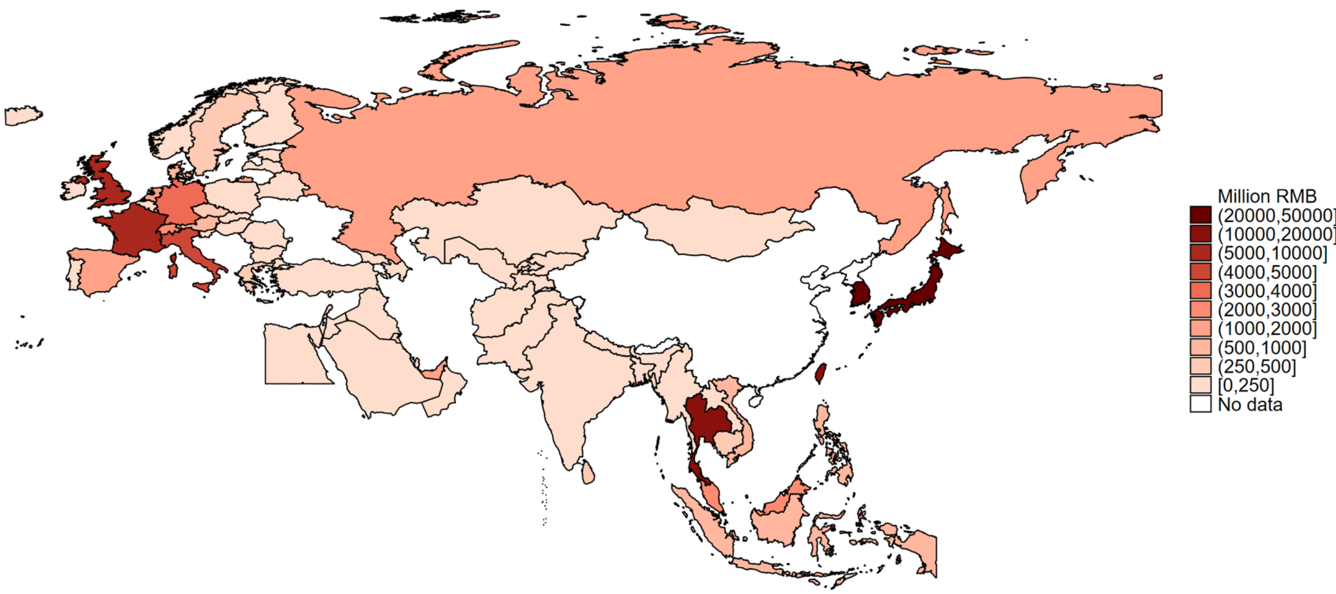

Notes: The value of transactions is in millions RMB. The map shows the change in the total value of transactions between 2011 and 2016 in the cities in mainland China.

particularly in 29 cities where the card transaction value increased by more than one billion RMB. The cities that experienced the largest growth are Shanghai (by 28.2 billion RMB), Beijing (by 22.5 billion RMB), and Shenzhen (by 8.0 billion RMB). Interestingly, the large growth of the transaction values is observed not only in the cities in Eastern China but also in inland regions such as Chengdu, Wuhan, and Chongqing. For example, total overseas transactions in Wuhan (an inland city in Hubei Province) increased by around 672.8%, from 440.7 million to over 3.4 billion RMB.

We also map the change in the total value of transactions across destination countries (Figure 3). All countries received more value of transactions in 2016 than in 2011. The countries with the most substantial increase in card transaction value are Japan (by 41.1 billion RMB), Korea (by 32.3 billion RMB), and Thailand (by 17.3 billion RMB). We observe a significant rise in transactions even in countries farther from China. For example, 15 countries experienced growth of more than one billion RMB, and eight of them are in Europe, including the UK, France, Italy, and Germany.

**Fact 2: Improvement in air connectivity**

Figure 3: Change in Card Transaction Values from 2011 to 2016 in Destination Countries




Notes: The value of transactions is in millions RMB. The map shows the change in the total value of transactions in each country in our sample.

We measure air connectivity using the weekly frequency of direct flights (i.e., the number of direct flights per week) at the city-country-year level. The improvement in air connectivity affects spending by Chinese travelers in two ways: (i) more frequent international direct flights on existing flight routes (i.e., intensive-margin effect), and (ii) the opening of new direct flight routes (i.e., extensive-margin effect).

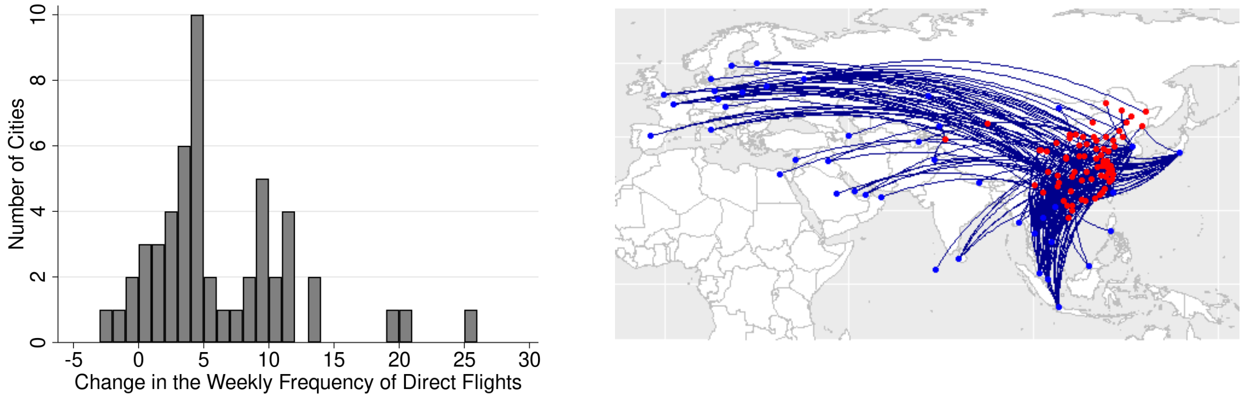
To analyze the intensive-margin effect, we restrict our sample to the flight routes that exist in 2011, and compare the average weekly frequency at the city level between 2011 and 2016.[14] Panel (a) of Figure 4 shows the distribution of the increase in average frequency in 2016 compared to 2011. There are 52 cities with at least one international flight route in 2011. On average, airlines operate additional 6.25 flights per week on existing air routes in 2016. In particular, air connectivity in Qingdao has dramatically improved through the intensive-margin effect, with an increase of 25.55 flights per week in 2016 compared to 2011.[15]

For the extensive-margin effect, Panel (b) of Figure 4 illustrates the new direct flight routes that opened over our data period. Between 2011 and 2016, there were 272 new di-

[14]Flight routes are defined at the city-country level. We take the average frequency within each city.

[15]The most frequent flight routes from Qingdao are those to Korea and Japan. Four airlines operated more than two flights to Korea every day in 2016.

Figure 4: Improvements in Air Connectivity Between Chinese Cities and Foreign Countries




(a) Distribution of the Change in the Weekly Frequency in 2011-2016

(b) New Direct Flight Routes

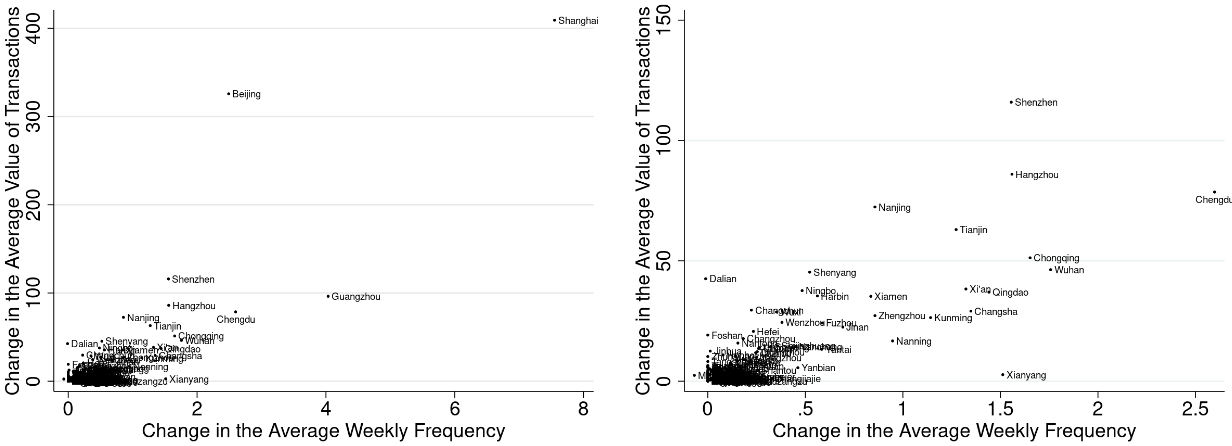
Notes: Panel (a) shows the distribution of the number of Chinese cities with the change in the average weekly frequency of direct flights between 2011 and 2016. We focus on the cities with at least one international direct flight in 2011. Before considering the difference from 2011 to 2016, we calculate the average weekly frequency of direct flights within each city. In Panel (b), the dark blue lines show the new direct flight routes from Chinese cities (with red dots) to destination countries (with blue dots) opened after 2011.

rect flight routes, and Chinese cities were connected with 1.41 new destinations on average. Among the 73 cities with at least one new flight route, Chengdu attracted the largest number of new routes as it was newly connected with 14 countries in 2016 compared to 2011. The most frequent direct flight route from Chengdu is bound for Vietnam, with a 21.10 weekly frequency in 2016. Additionally, Thailand attracted the largest number of new routes, which are connected with 39 cities.

**Fact 3: Positive relationship between air connectivity and card transaction values** We observe the increase in the value of transactions using card transaction data (Fact 1) and the development of air connectivity using flight data (Fact 2). Now, we combine the two datasets and analyze the relationship between these two facts.

We first calculate the average values of transactions and the weekly frequency of direct flights at the city-year level, and take the difference between 2011 and 2016. We then plot the difference in the average transaction values on the x-axis and that in the average weekly frequency on the y-axis (Figure 5). In Panel (a), we observe a positive correlation, which suggests that Chinese travelers in cities with improvements in air connectivity spent more

Figure 5: Change in Air Connectivity and the Value of Transactions




(a) All Chinese Cities

(b) Excluding Three Cities

Notes: Panel (a) and Panel (b) show the correlation between the change in the value of transactions between 2011 and 2016 (on the y-axis) and the change in the weekly frequency of direct flights from 2011 to 2016 (on the x-axis). We calculate the average value of transactions and frequency of direct flights within each city. We exclude Shanghai, Beijing, and Guangzhou to focus on other Chinese cities in Panel (b).

overseas. We observe that major cities such as Shanghai, Beijing, and Guangzhou experienced a larger increase both in air connectivity and transaction values. Even when we exclude these three cities, a positive relationship between air connectivity and card transaction values persists (Panel (b)).[16] In the subsequent sections, we empirically investigate these positive relationships.

# 3 Model and Empirical Strategy

In this section, we present a model that explains the flow of traveler spending from Chinese cities to foreign countries. We then derive the equation for our regressions from the model.

## 3.1 Model

Our model is based on Head et al. (2008), who introduce a gravity-type equation for bilateral service trade. Each foreign country offers amenities for travelers, and a consumer makes a

[16] In the regression analysis in Section 4.1, we exclude the transactions from Shanghai and Beijing for a robustness check. The result is almost identical to the main regression with all Chinese cities.

discrete choice among her possible destinations based on her preferences. We refer to Farber and Gaubert (2019) to set up consumers' utility for international travel.

**Consumer Preferences**:

A representative consumer who lives in a Chinese city, $i$, receives the following utility through the consumption of goods and services in sector $\omega \in \{0, 1, ..., \Omega\}$ :

$$U_i = \sum_{\omega=0}^{\Omega} \beta_i^{\omega} \ln C^{\omega},$$

where $\sum_{\omega=0}^{\Omega} \beta_i^{\omega} = 1$ and $\beta_i^{\omega} \geq 0$.

We have a timing assumption to consider the consumer's choice problem. First, a consumer sets her budget for goods and services in each sector, and next she decides on the detailed types of products she wishes to consume. We assume one of the $\omega$s denotes the index for the tourism and travel-related services sector, and we omit that indicator in the following equations. The Cobb-Douglas utility function implies that a consumer in $i$ spends $X_i = \beta_i Y_i$ on travel. $Y_i$ is the aggregate income of a Chinese city, $i$. Given this budget for travel, a consumer decides her destination and visits there to consume travel-related services.

A consumer in city $i$ receives the following utility in destination country $j$:

$$\ln C_{ij} = \ln \frac{a_j q_{ij}}{\tau_{ij}},$$

where $a_j$ is the amenity that each destination provides to a consumer, $q_{ij}$ is the quantity of travel services and goods, and $\tau_{ij}$ is the iceberg travel costs. The quantity of consumption is $q_{ij} = X_i/p_j = \beta_i Y_i/p_j$, and $p_j$ is the price of travel services and goods in the destination, $j$. We restate the utility from travel:

$$\ln C_{ij} = \ln \frac{a_j \beta_i Y_i}{\tau_{ij} p_j} = \ln a_j + \ln \beta_i + \ln Y_i - \ln \tau_{ij} - \ln p_j. \tag{1}$$

**Tourism Service Technology**:

There are $J$ foreign countries, and each country offers a different level of amenity, $a_j$, to each traveler. We assume that $a_j$ has a Fréchet distribution with the cumulative distribution function (CDF):

$$G_j(a) = exp(-(a/A_j)^{-\theta}),$$

where $A_j$ is a country-specific attractiveness as a travel destination, and $\theta$ is a dispersion parameter that is common to all destinations. If $a_j$ is distributed Fréchet, $\ln a_j$ has the Gumbel distribution (the type-I generalized extreme value distribution), and its CDF is $\hat{G}_j(\ln a) = \exp[-\exp(-\theta(\ln a - \ln A_j))]$. Assume there are $N_j$ locations to visit in each country $j$. Each traveler draws her idiosyncratic preference shock for each location and decides which location she visits as the main destination in country $j$. The maximum of $N$ draws from the the Gumbel distribution, $\hat{G}_j(\ln a)$, has the double exponential distribution: $\exp[-\exp(-\theta(\ln a - \ln A_j - (1/\theta)\ln N_j))]$. Using equation 1, the expected utility through traveling to country $j$ from city $i$ is:

$$E[\ln C_{ij}] = \ln A_j + (1/\theta)\ln N_j + \ln \beta_i + \ln Y_i - \ln \tau_{ij} - \ln p_j + \epsilon_{ij},$$

where $\epsilon_{ij}$ is i.i.d. with the Gumbel distribution and its CDF is $\exp(-\exp(-\theta\epsilon))$. According to Anderson et al. (1992, p.39), the choice probability takes the multinomial logit formula[17]:

$$\pi_{ij} = \frac{\exp[\ln N_j + \theta(\ln A_j + \ln \beta_i + \ln Y_i - \ln \tau_{ij} - \ln p_j)]}{\sum_{j=1}^{J} \exp[\ln N_j + \theta(\ln A_j + \ln \beta_i + \ln Y_i - \ln \tau_{ij} - \ln p_j)]}.$$

This choice probability shows that the fraction of consumers in $i$ that travel to $j$ increases in the size of Chinese cities and destinations, $Y_i$ and $N_j$, and also in the attractiveness of travel destination $j$, $A_j$. Conversely, the probability decreases in the travel costs, $\tau_{ij}$, and the price in the destination, $p_j$.

**Bilateral Flow of Traveler Spending**:

The expected bilateral flow of transactions by travelers from city $i$ to destination $j$ is

$$X_{ij} = \pi_{ij} X_i,$$

[17] It is because the probability that a consumer in city $i$ chooses $j$ as her travel destination will converge by the law of large numbers, as the number of foreign countries, $J$, is sufficiently large

where $X_i$ is the total traveler spending in city $i$ such that $X_i = \sum_{j=1}^{J} X_{ij}$. Using $X_i = \beta_i Y_i$ and adding a year subscript, $t$, the expected flow of traveler spending from city $i$ to destination $j$ in year $t$ is

$$X_{ijt} = N_{jt} A_{jt}^{\theta} (\beta_{it} Y_{it})^{1+\theta} (\tau_{ijt} p_{jt})^{-\theta} \Phi_{it}^{\theta}, \tag{2}$$

where $\Phi_{it} = \left[ \sum_{j=1}^{J} N_{jt} \left( \frac{\tau_{ijt} p_{jt}}{A_{jt} \beta_{it} Y_{it}} \right)^{-\theta} \right]^{-\frac{1}{\theta}}$.

**Air Connectivity**:

There are two types of costs for consumers to travel to their destination countries: one is time-varying—the degree of air flight connectivity between Chinese city $i$ and foreign country $j$—while the other is time-invariant—characteristics that are common to $i$ and $j$, such as language barriers. We can express the total trade costs, $\tau_{ijt}$, as

$$\tau_{ijt} = D_{ijt} \; e^{\alpha_{ij}}, \tag{3}$$

where $D_{ijt}$ is air flight connectivity at $t$, and $\alpha_{ij}$ is common characteristics between $i$ and $j$.

Taking logs of the variables in equation 2 and using equation 3, we obtain the equation that represents the log of the expected trade flow in traveler spending from Chinese city $i$ to country $j$ in year $t$:

$$\ln X_{ijt} = \underbrace{(1+\theta)\ln \beta_{it} + (1+\theta)\ln Y_{it} + \theta \ln \Phi_{it}}_{\text{Chinese city effects}} + \underbrace{\theta \ln A_{jt} - \theta \ln p_{jt} + \ln N_{jt}}_{\text{destination effects}} - \underbrace{\theta \ln D_{ijt} - \theta \alpha_{ij}}_{\substack{\text{city-destination} \\ \text{effects}}}. \tag{4}$$

This equation shows that the flow of traveler spending in year $t$ depends on effects specific to Chinese city $i$, effects specific to foreign destination $j$, and the origin-destination effects of travel costs.

## 3.2 Model Implementation: OLS Estimation

Equation 4 represents the expected value of transactions made by travelers from Chinese city $i$ to foreign country $j$. We add an error term, $\epsilon_{ijt}$, that captures measurement error in card transactions to equation 4, and use the resulting equation to estimate the empirical relationship between card transactions and air connectivity.

A notable challenge in our data is the presence of substantial zero values in transaction values $X_{ijt}$ and weekly frequency of direct flights $D_{ijt}$. We apply the inverse hyperbolic sine (or arcsinh) transformation to both variables to address this issue.[18] This transformation approximates the natural logarithm of the variables while allowing for zero observations.

Our baseline regression specification is

$$\tilde{X}_{ijt} = \gamma_0 + \gamma_1 \tilde{D}_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}, \tag{5}$$

where $\tilde{X}_{ijt}$ denotes the value of total card transactions by Chinese travelers from city $i$ in country $j$, and $\tilde{D}_{ijt}$ is the level of air connectivity (i.e., weekly frequency of direct flights between $i$ and $j$). The inverse hyperbolic sine transformation has been applied to both variables, $\tilde{X}_{ijt}$ and $\tilde{D}_{ijt}$. The estimated coefficient can be approximated to the elasticity, which is the ratio of the percentage change in the transaction value to the percentage change in the weekly frequency of direct flights (Bellemare and Wichman 2020).[19]

We include city-country fixed effects $\delta_{ij}$ to capture time-invariant unobserved heterogeneity that induces consumers in $i$ to visit $j$, including cultural and business relationships. Origin-city time-varying fixed effects $\eta_{it}$ account for origin-specific time-variant factors, such as city income. Additionally, destination-country time-varying fixed effects $\kappa_{jt}$ control for the inward multilateral resistance and unobserved destination-specific time-variant factors, such as tourist attractions and the price of travel services and goods.

Based on our descriptive analysis in Section 2.3, we expect that the improvement in air connectivity will increase the number of travelers, and thus the value of card transactions will rise as well. In other words, we expect the coefficient of interest, $\gamma_1$, to be positive. In all our regressions, we cluster standard errors at the city-country level.

[18] The formula for the inverse hyperbolic sine transformation is $\tilde{x} = arcsinh(x) = \ln(x + \sqrt{x^2 + 1})$. Alternatively, we could employ the Poisson Pseudo Maximum Likelihood (PPML) regression to address zero values. See footnote 27 for further details.

[19] Bellemare and Wichman (2020) show that the estimated coefficient becomes more stable as the sizes of dependent and independent variables get larger. Although the size of our explanatory variable (the weekly frequency of direct flights) might be small, their Monte Carlo simulations also indicate that any bias in the estimated coefficient is negligible and does not significantly affect our findings.

### 3.3 Endogeneity and IV Approach

Our goal is to identify the effect of air connectivity on the spending of Chinese consumers in foreign countries. However, the OLS estimator, $\gamma_1$, from equation 5 is likely endogenous. Direct flights to a foreign country are not randomly assigned to Chinese cities. Rather, air connectivity is likely greater between city-country pairs that have pre-existing high travel demand and would have had a greater demand for travel and higher levels of card transactions even without an air connection. This raises a reverse causality concern—a larger value of transactions might improve flight connectivity, instead of better flight connectivity increasing the value of transactions.

#### 3.3.1 Designing an Instrumental Variable

We introduce a unique instrumental variable (IV) to overcome this endogeneity concern. Our instrument exploits plausibly exogenous variation in air connectivity across destination countries as a predictor of the direct flights between a city-country pair. Formally, the IV is

$$Z_{ijt} = \lambda_{jt} \times \ln dist_{ij}, \tag{6}$$

where $\lambda_{jt}$ is the global share of total international flights (excluding China) for which country $j$ is the origin ($\lambda_{jt} = \frac{flight_{jt}}{\sum_j flight_{jt}}$), and $\ln dist_{ij}$ is the natural logarithm of the geographical distance between Chinese city $i$ and country $j$.[20] The numerator of $\lambda_{jt}$ is the total number of direct flights departing from country $j$ in year $t$, and the denominator is the total number of international flights departing from all countries around the world in year $t$. We exclude flights arriving in and departing from China both in the numerator and denominator. Multiplying the distance between city $i$ and country $j$, $dist_{ij}$, by the country-year level share $\lambda_{jt}$, gives the city-country-year level variation for our instrumental variable.

The interaction term in our IV represents the differential impact of an airport expansion in a foreign country between two groups of travelers: those in Chinese cities close to the

[20] When constructing the value $\lambda_{jt}$, we use outbound flights departing from foreign countries (excluding flights arriving in and departing from China), while our explanatory variables (i.e., the weekly frequency of direct flights) are based on inbound flights departing from China. Using outbound flights can provide a more exogenous instrument.

foreign country, and those in cities farther away. There are fewer flights connecting more distant markets, in general (Cristea 2023). Airline companies face higher trade costs for more distant markets, and therefore the impact of the air transportation development in destination countries can be attenuated by distance.[21] Our instrument is expected to be negatively correlated with the frequency of direct flights, $\tilde{D}_{ijt}$: a country with a comparative advantage in air transportation is more likely to have direct flights, while city-country pairs that are farther apart likely have fewer direct flights connecting them. We assume that distance affects our dependent variable (value of card transactions) only through air connectivity (our endogenous variable) conditional on the origin-destination FEs.[22]

While our IV differs from a shift-share instrument because distance is not a share, the motivation for our IV is similar to the shift-share IV developed by Autor et al. (2013). The authors instrument for the change in US imports from China using other countries' imports from China (i.e., a shock to China's comparative advantage in productivity) and employment shares in regions. The employment shares allow the authors to allocate the impact of the shock to each region. In contrast to Autor et al. (2013), we instrument for Chinese air connectivity using other countries' air connectivity (i.e., a shock to the comparative advantage in air transportation technology in a foreign country) and trade costs (i.e., the distance between a foreign country and a Chinese city). We use trade costs to assign the impact of the improvement in air connectivity to each Chinese city.

### 3.3.2 Identification Assumption

Our key identifying assumption is that the share of the flights departing from country $j$, $\lambda_{jt}$, is uncorrelated with demand shocks in a particular Chinese city for travel to that country in year $t$. We argue that the relevant exclusion restriction holds because foreign governments—not Chinese city governments—develop destination countries' levels of air connectivity. As such, the degree of a foreign country's air connectivity is plausibly exogenous with respect to the characteristics of Chinese origin cities that might influence demand for travel, except

[21] In airline markets in particular, regulations stipulate how long pilots can work on flights, which increases the costs of long-distance air connections (Campante and Yanagizawa-Drott 2017).

[22] There are origin-destination fixed effects, $\delta_{ij}$, in our main regression, which should address other concerns for our identification strategy.

Table 2: Share of Flights from China to Destination Countries in 2011 and 2016

| Country | Share 2011 (%) | Share 2016 (%) | $\hat{\lambda}$ (%) |
|---|---|---|---|
| Iraq | 0 | 0.25 | 148.44 |
| Myanmar | 15.64 | 10.13 | 115.11 |
| Saudi Arabia | 0.16 | 0.21 | 52.45 |
| Qatar | 1.41 | 1.44 | 42.78 |
| Vietnam | 10.42 | 13.72 | 40.06 |
| Kyrgyzstan | 8.62 | 5.59 | 36.76 |
| Oman | 0 | 0.03 | 35.59 |
| Turkey | 0.60 | 0.47 | 33.39 |
| Taiwan | 23.68 | 24.65 | 32.81 |
| Pakistan | 1.32 | 1.22 | 31.69 |
| South Korea | 28.73 | 31.53 | 31.09 |
| United Arab Emirates | 1.59 | 1.43 | 28.00 |
| Japan | 21.31 | 22.85 | 26.82 |
| Laos, PDR | 15.84 | 14.12 | 20.74 |
| Israel | 0.48 | 0.51 | 18.57 |

Note: This table shows the share of flights from China to the countries that experience the largest change in the global share of international flights departing from country $j$ (the part of our IV, $\lambda_{jt}$). We select the top 15 countries with the largest change in $\lambda_{jt}$. We exclude countries without any direct flights from China both in 2011 and 2016 because those countries do not affect our regression results due to city-country fixed effects (e.g., no time variation in the weekly frequency of direct flights from Chinese cities to those countries).

insofar as greater air connectivity in a destination country increases the probability that a given Chinese city is connected to that foreign country.

To illustrate the logic of our IV, consider the example of the United Arab Emirates (UAE). The UAE government paid increasing attention to air transportation as one of its major sources of economic development.[23] The country opened the world's largest airline terminal in Dubai in 2008. Since then, its share of global international direct flights (i.e., the first term in our instrumental variable) has increased substantially. The number of flights arriving in the UAE increased by 52.7% between 2011 and 2016. This and similar government efforts to attract direct flights depend on investment decisions by local governments, not shocks

[23]Source: Statistical Yearbook of Abu Dhabi 2017 (link; accessed on November 5, 2022).

to travel demand in particular Chinese cities. Similar airport expansion and improvements in air connectivity have occurred around the world during our sample period, including the UK, Turkey, Spain, and Saudi Arabia (Appendix A.3).

Table 2 shows the top 15 countries experiencing the largest increase in the part of our IV, $\lambda_{jt}$ (the global share of flights departing from a country $j$, excluding flights coming to China). We also provide the share of flights from China to those countries in 2011 and 2016 (e.g., the number of flights coming from China to a country over the total flights arriving in that country). Notably, the share of flights arriving from China has not significantly increased despite improvements in the air transportation networks across all listed countries. For example, while the global share of flights departing Iraq and Myanmar increased by over 100%, the share of flights from China to Iraq was zero in 2011 and only 0.25% in 2016. For Myanmar, the share even decreased from 15.64% in 2011 to 10.13% in 2016. This indicates that the objective of improving air connectivity was to attract travelers from all over the world, rather than specifically targeting Chinese travelers. The variation in air transportation development is plausibly exogenous to demand shocks from Chinese cities and thus serves as a valid instrument for our analysis.

## 3.4 2SLS Specification

Using our IV, we estimate the following two-stage least squares (2SLS) system to obtain the causal effect of air connectivity on Chinese card transactions in a foreign market:

$$\tilde{D}_{ijt} = \alpha_0 + \alpha_1 Z_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \xi_{ijt} \qquad \text{(first stage)} \tag{7}$$

$$\tilde{X}_{ijt} = \gamma_0 + \gamma_1 \tilde{D}_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}, \qquad \text{(second stage)} \tag{8}$$

where we define $Z_{ijt}$ in equation 6. Our first stage coefficient, $\alpha_1$, captures the relationship between the global share of flights departing from foreign country $j$, as well as the distance between $j$ and Chinese city $i$ (together making up our IV, $Z$), and the degree of air connectivity between city $i$ and country $j$, $\tilde{D}$. In these terms, the exclusion restriction we describe above holds if our IV—$Z$—is uncorrelated with other unobserved determinants of card transaction values between $i$ and $j$, $\epsilon$. Our second stage coefficient of interest, $\gamma_1$, delivers the causal impact of air connectivity on card transactions made by consumers from city $i$ in destination country $j$.

# 4 Results

We estimate the impact of air connectivity on traveler spending using our linked flight-Chinese card transaction data and our IV framework. We first report 2SLS results, using the equations we define in Section 3.4, that show how direct air routes affect the flow of visitor spending. We then analyze the robustness of our estimates to different specifications and measure of air connectivity. In the last subsection, we forecast the potential impact of a new airport opening on traveler spending using our estimated coefficient.

## 4.1 Main Result

In our main specification, we analyze the effect of the improvement in the weekly frequency of direct flights on card transaction values. Column 2 of Table 3 shows the IV regression result with the inclusion of three types of fixed effects (FEs): origin-specific time-varying FEs, destination-specific time-varying FEs, and city-country pair FEs. The IV coefficient on the frequency of direct flights is positive and significant. Specifically, a 1% increase in the weekly frequency of direct flights leads to a 1.97% increase in cross-border travel spending. The average weekly frequency of direct flights is 3.75 over the data period.[24] Intuitively, our regression suggests that in a city with the average weekly frequency, if an airline offers one additional weekly direct flight, the travelers in that city spend 52.45% more in that destination country. We report first-stage results at the bottom of the table. The coefficient on the IV is negative and highly significant. More importantly, the first-stage F statistic is 24.27, which suggests that we can reject the null of a weak instrument.[25]

The IV coefficient is larger than the OLS coefficient reported in column 1. This downward bias does not preclude potential reverse causality, but it does suggest there is a stronger

[24] We focus on the cities with at least one direct flight over the data period to obtain the average frequency at the city level.

[25] The IV satisfies another test for verification. The Kleibergen-Paap LM statistic rejects the null that the model is unidentified.

Table 3: Main Results

| | Transaction value | | |
|---|---|---|---|
| | Baseline sample | | Excl. big cities |
| | OLS | 2SLS | 2SLS |
| | (1) | (2) | (3) |
| Weekly Frequency | 0.064*** | 1.967*** | 2.028*** |
| | (0.023) | (0.476) | (0.478) |
| Origin city-year FEs | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes |
| Observations | 59,154 | 59,154 | 58,314 |
| First Stage | | | |
| IV | | −39.045*** | −39.869*** |
| | | (7.926) | (7.971) |
| KP Wald rk $F$-statistic | | 24.268 | 25.020 |
| KP LM statistic | | 24.519 | 25.302 |
| KP LM $p$-value | | 0.000 | 0.000 |
| AR Wald test $p$-value | | 0.000 | 0.000 |

Notes: Columns 1 and 2 show the baseline results. In column 3, we drop the city-country pairs that include Shanghai or Beijing. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

negative force diminishing the relationship between air connectivity and the value of card transactions. The difference between our 2SLS and OLS coefficients underscores the distinction between the "treatment" in our OLS and 2SLS specifications, and their effects on demand for travel. Our 2SLS estimator captures the local average treatment effect (LATE) of a *new* direct flight on card transactions; the OLS estimator captures the correlation between an *existing* direct flight, one that may have been operated for many years, on card transactions. A new flight likely causes a spike in demand, which is the object of interest for us, but that effect may wear off over time—hence, the average existing flight has less of an influence on demand for travel than a brand new flight. For our setting, the time variation of IV for a given city-country pair relies on an exogenous variation of the destination country in its world share of international direct flights (the share $\lambda_{jt}$ in equation 6).

In column 3, we limit our sample size to check if the result differs substantially based on a different sample selection. One potential issue is that most Chinese international travelers are from Shanghai and Beijing, and therefore our estimate may be largely driven by the travelers from these two cities.[26] We delete the city-country pairs that include Shanghai or Beijing and re-estimate our 2SLS specifications to see whether our findings hold in this restricted sample. Column 3 of Table 3 shows that the 2SLS coefficients with the restricted sample are very similar to the ones with the full sample (shown in columns 2 of Table 3) in terms of size, significance, and sign. These results suggest that our estimates are not specific to the two largest Chinese cities.

## 4.2 Robustness Checks

Our IV regressions show that an increase in the number of weekly direct flights from a city to a country positively affects the value of card transactions between that city-country pair. We test whether our main result (column 2 of Table 3) is robust to alternative specifications.[27]

### 4.2.1 Alternative Specifications with Weekly Frequency of Direct Flights

One of the robustness checks is to employ different specifications for our data sample. First, we examine how our results change when we expand the scope of Chinese cities in our sample. We have so far focused on cities that had airports during our sample period and

[26] Table A.2 shows that the largest flows originate from the largest Chinese city (i.e., Shanghai and Beijing) to the largest economies with closer proximity (i.e., Japan, South Korea, and Taiwan). One might be concerned that the transaction values are concentrated so much between these city-country pairs. However, we observe that the shares of these city-country pair transactions are small, and therefore omitting the top origin-destination pairs does not affect our analysis. Put differently, our analysis is not driven by the extensive travel between Beijing and Shanghai and nearby countries (Japan and South Korea).

[27] One of the possible robustness checks is conducting a Poisson Pseudo Maximum Likelihood (PPML) regression instead of using the inverse hyperbolic sine transformation. We apply the control function method to run a PPML regression with our IV and fixed effects because no Stata command is available for a PPML regression with IV and fixed effects. In the control function method, we first regress our endogenous variable (the weekly frequency of direct flights) on our IV and fixed effects, and generate the error term. In the next step, we regress our dependent variable (the value of transactions) on the predicted error term, the endogenous variable, and fixed effects. The result shows that both the coefficients on the weekly frequency of direct flights (the coefficient of our interest) and the residual are insignificant, which suggests no endogeneity concerns in this PPML specification (i.e., Hausman test). In the PPML regressions without IV, the coefficient of our interest is 0.055 and significant at the 1% level.

Table 4: Regressions with Different Variables and Specifications

| | Transaction value | | |
|---|---|---|---|
| | Cities w/o airports<br>2SLS<br>(1) | European regions<br>2SLS<br>(2) | Nearby airports<br>2SLS<br>(3) |
| Weekly Frequency | 4.068*** | 1.869*** | 1.726*** |
| | (1.095) | (0.434) | (0.349) |
| Origin city-year FEs | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes |
| Observations | 100,296 | 59,154 | 100,296 |
| First Stage | | | |
| IV | −22.386*** | −41.087*** | −52.761*** |
| | (5.621) | (7.896) | (10.213) |
| KP Wald rk $F$-statistic | 15.862 | 27.079 | 26.688 |
| KP LM statistic | 16.052 | 27.203 | 27.119 |
| KP LM $p$-value | 0.000 | 0.000 | 0.000 |
| AR Wald test $p$-value | 0.000 | 0.000 | 0.000 |

Notes: In column 1, we include cities without airports in our baseline sample. In column 2, we group European countries into four regions (Central and Eastern Europe, Northern Europe, Southern Europe, and Western Europe). In column 3, we consider all airports located within 200 km of each Chinese city. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

analyzed the effect of the number of weekly direct flights on overseas travel spending. Here, we include the additional group of Chinese cities—cities that do not have airports. If we include those cities in our sample, we expect that the size of the coefficient of interest will be larger than our main result because our baseline group would be cities without access to air transportation, instead of cities without access to international flights. Our results after including cities without airports appear in column 1 of Table 4. The coefficient of the 2SLS estimate is positive and significant, and as expected, the size is larger than the coefficient in our main result (shown in column 2 of Table 3) because it includes the variation of air connectivity due to an establishment of airports.

In addition, we take into account that Chinese travelers possibly visit other countries close to their first arrival countries. This concern is especially relevant to travel in European countries, where multiple destinations can be easily accessible. To address this issue, we group European countries into four geographical regions and measure the frequency of direct flights for each European region.[28] Column 2 of Table 4 shows the result of this alternative regression, and the coefficient closely aligns with our main regression result.

We also consider a scenario where Chinese travelers have the option to use airports located in neighboring cities. We assume that travelers are willing to drive up to 200 km to access other airports, meaning we consider all flights departing from airports within a 200 km radius from the center of a city.[29] In other regressions, Chinese travelers access only the international direct flights departing from their residing cities. However, in this alternative specification, travelers can benefit from flights departing from nearby cities. Since travelers are endowed with a larger set of international flights, the impact of a new international flight route becomes less influential. The regression result supports this assumption, as we observe a smaller coefficient on the weekly frequency of direct flights (column 3 of Table 4).

#### 4.2.2 Travel Time

We consider travel time from Chinese cities to foreign countries as an alternative measure of air connectivity. While we considered only international direct flights in the main specification, we now include indirect flight connections to travel to destination countries. The procedures to measure travel time are outlined in Section 2.1 and Appendix Section B. The unit of travel time is an hour.

The result of the IV regression is presented in column 2 of Table 5. The coefficient of travel time is 3.83 and significant at the 1% level, which indicates that a 1% decrease in travel time leads to a 3.83% increase in the value of transactions. The average travel time is 13.39 hours in our data. Our result suggests that if travelers in a city with the average travel time can reach a foreign country an hour faster than before, the transaction value will increase by 28.60% in this city-country pair. We observe a similar statistically significant coefficient even when excluding Beijing and Shanghai from our sample (column 3 of Table

[28]According to the European Union, the regions are defined as follows: Central and Eastern Europe, Northern Europe, Southern Europe, and Western Europe.

[29]We identify nearby airports within a 200 km radius using the longitudes and latitudes of cities.

Table 5: Regressions with Travel Time

| | Transaction value | | |
|---|---|---|---|
| | All cities | | Excl. big cities |
| | OLS | 2SLS | 2SLS |
| | (1) | (2) | (3) |
| Travel Time | −0.157*** | −3.834*** | −4.038*** |
| | (0.025) | (1.443) | (1.487) |
| Origin city-year FEs | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes |
| Observations | 46,554 | 46,554 | 45,714 |
| First Stage | | | |
| IV | | 16.046*** | 16.390*** |
| | | (5.630) | (5.687) |
| KP Wald rk $F$-statistic | | 8.122 | 8.304 |
| KP LM statistic | | 8.150 | 8.329 |
| KP LM $p$-value | | 0.004 | 0.004 |
| AR Wald test $p$-value | | 0.000 | 0.000 |

Notes: We use travel time, instead of the weekly frequency of direct flights in the regressions. Columns 1 and 2 show the main results with travel time. In column 3, we exclude the city-country pairs that include Shanghai or Beijing. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

5).

Opening a new direct flight route not only shortens the travel time to the country connected directly by the flight but also indirectly reduces the travel time to the third country. For example, there was no direct flight from Chongqing to the UK between 2011 and 2015. In 2011, the flight route with the shortest duration was flying from Chongqing to Beijing, and then taking a flight from Beijing to the UK. However, in 2012, a new flight route from Chongqing to Finland opened, which enabled travelers to reach the UK through Finland. The direct flights to Finland reduced travel time to the UK by an hour. Finally, in 2016, another new direct flight from Chongqing to the UK began, which allowed travelers to visit the UK four hours faster without any connections.

Now, we consider the effect of a new direct flight route on the value of transactions. In our data, a new direct flight route reduces travel time by 1.77 hours on average.[30] Our result suggests that a one-hour reduction in travel time leads to a 28.60% increase in transaction values, and thus, the introduction of a new air route can potentially boost transaction values by 50.62% (28.60×1.77=50.62%). This estimate is similar to the one from the main result (i.e., one additional weekly frequency of direct flight increases the transaction value by 52.45%). Given that a new flight route increases at least one weekly frequency of direct flights, our main result is robust to the alternative specification using travel time.

One may notice that the first-stage F statistic with travel time is lower than that with the frequency of direct flights. The variation of our IV relies on airport expansions in destination countries, which captures the probability that more frequent or new direct flights will open to the destination countries with airport expansions. As mentioned earlier, new direct flights can indirectly affect the time to travel to the third country (i.e., travelers from Chongqing start flying to the UK via a new direct flight to Finland), which weakens the explanatory power of our IV for travel time.

## 4.3 Policy Implications

Our main result indicates that a 1% increase in the weekly frequency of direct flights increases the value of transactions by 1.97%. This information helps policymakers evaluate the impact of improving air transportation facilities on inbound visitor spending. In this section, we focus on the new airport opening in Turkey and compare the amount of investment to the estimated benefits from travelers' spending. Istanbul Airport in Turkey opened in October 2018 and started operating all passenger flights in April 2019. This new airport became the busiest airport in Europe, with six runways and the capacity to accommodate 500 aircraft.

This expansion in air transportation capacity led to three new flight schedules between Chinese cities and Istanbul. Specifically, China Southern Airlines launched new flight routes from Istanbul to Beijing in December 2018 and to Wuhan in May 2019. Additionally, China's Sichuan Airlines began a new flight schedule connecting Chengdu to Istanbul in April 2019.

[30] On average, a new flight route reduces travel time by 3.31 hours by providing a non-stop flight to a destination (i.e., direct effect), while it enables a traveler to save an hour using the new non-stop destination as a transit airport (i.e., indirect effect).

Before the new airport opening, Turkish Airlines operated direct flights between Beijing and Istanbul every day, and therefore, the new three-weekly flight schedule increased the weekly frequency of direct flights from 7 to 10.

We forecast the impact of the additional three-weekly flights to Beijing on travelers' spending. We obtain the projected transaction value for 2019, $X_{2019}$, using the equation:

$$X_{2019} = X_{2016} \times (1 + 1.97\Delta_{frequency}),$$

where $X_{2016}$ is the value of card transactions in 2016 (observed in our dataset), $\Delta_{frequency}$ is the change in the weekly frequency of direct flights, and 1.97 is the coefficient in column 2 of Table 3. Because the frequency increased from 7 to 10, $\Delta_{frequency} = (10 - 7)/7 = 0.43$. We estimate that the transaction value is projected to increase by 5.18 million USD after the new airport opening in 2019 (i.e., $X_{2019} - X_{2016} = 5.18$).

How much did Turkey invest to attract additional direct flights from Beijing? The total investment in Istanbul Airport amounted to 12 billion USD. The additional flights from Beijing to Istanbul account for 2% of the total new flights from all overseas airports to Istanbul in 2019. Although the long-term economic benefits are challenging to estimate, we refer to the cost and benefit analysis for the Heathrow Airport expansion made by the UK government and consider that the new airport will contribute to the economy for 60 years.[31] The estimated expense for Turkey to acquire new travelers from Beijing in 2019 is 4 million USD (12 billion USD/60 years $\times$ 0.02), which is lower than the estimated benefits from travelers' spending (5.18 million USD as mentioned above). The new airport construction brings additional benefits other than visitor spending, including job creation and the enhancement of business relationships. Overall, our analysis suggests that the benefits from traveler spending can be substantial compared to the cost associated with air transportation improvements.

# 5 Further Analyses

We showed that the development of air transportation networks leads to an increase in inbound visitor spending using cross-border card transaction data. In this section, we further

[31] See Footnote 4 for the details.

investigate our findings with the value of card transactions by comparing them to the effect on trade in goods. Additionally, we study how shocks to consumer tastes and preferences toward destination countries affect traveler spending and trade in goods.

## 5.1 Trade in Goods

Improvement in air transportation networks affects not only consumer travel but also trade in goods. One may assume that an increase in travelers visiting abroad would have a positive spillover effect on imports of goods, particularly in the context of consumer goods. Travelers experience new products in countries they visit and may start purchasing the products after their trips. More direct flight connections increase the number of travelers, which in turn leads to an increase in imports of goods from countries with more frequent flight connections. Moreover, approximately half of air freight is shipped by passenger aircraft along with passengers and their baggage, although the amount of each shipment is small compared to cargo flights.[32] An increase in the weekly frequency of direct flights can affect trade in goods directly (by increasing freight capacity) and indirectly (by providing travelers with more exposure to foreign products).

Building on this idea, we extend our analysis to estimate the effect of air connectivity on imports of goods from country $j$ to Chinese city $i$ by running the IV regression introduced in Section 3.4. Specifically, we use the value of import as a dependent variable instead of the card transaction values (i.e., $\tilde{X}_{ijt}$ in equation 8).

We first examine the impact of air connectivity on the value of total imports, but the coefficient is not statistically significant (column 1 of Table 6). We further explore the effect on the imports of consumer goods, which are more relevant to consumption by travelers. The coefficient on the regression with the total value of imported consumer goods is not statistically significant (column 2 of Table 6), while the results vary across different industries, as illustrated in Figure 6. Specifically, we observe that the imports of food/beverages and pharmaceuticals/cosmetic products increase by around 1% with a 1% increase in the weekly

[32]For example, a Boeing 747-400, one of the largest passenger planes, can transport 5,330 cubic feet of cargo (the same amount can be transported by two semi-truck trailers) together with 416 passengers (link to the article; accessed on January 21, 2023). Also, see "Inbound air freight prices go sky high in the midst of pandemic," the US Bureau of Labor Statistics (link; accessed on January 21, 2023).

Table 6: Regressions with the Value of Imports

| | Value of imports | | |
|---|---|---|---|
| | Full Sample | Consumer goods | Non-consumer goods |
| | (1) | (2) | (3) |
| Weekly Frequency | −0.250 | 0.130 | −0.261 |
| | (0.465) | (0.338) | (0.459) |
| Origin city-year FEs | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes |
| Observations | 59,154 | 59,154 | 59,154 |

Notes: This table presents the results of IV regressions with the value of imports. The results of first-stage regressions are the same as those in column 2 of Table 3. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

frequency of direct flights.[33] It is worth noting that these products are mostly transported by air. For instance, food/beverages are perishable and time-sensitive products (Djankov et al. 2010). Similarly, pharmaceuticals have higher unit values compared to other products and are primarily shipped using a fast and expensive mode of transportation (Harrigan 2010).[34]

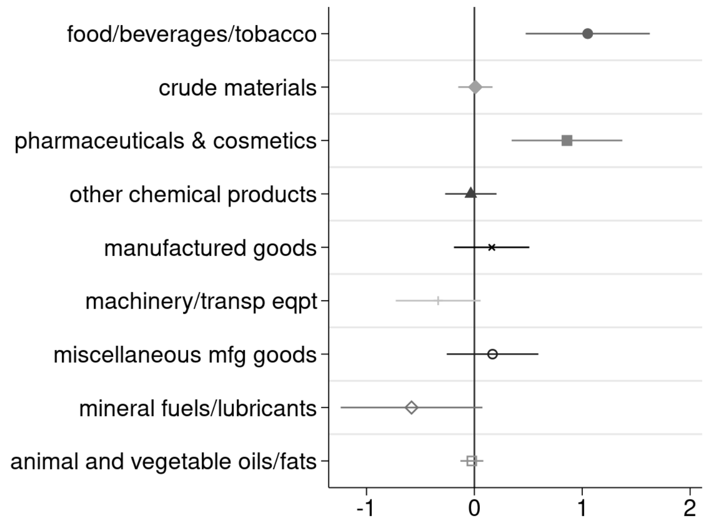
## 5.2 Effects of Political Conflicts

Unlike trade in goods, our model shows that costs to travel depend not only on trade costs (that we measure by air connectivity) but also on the amenities that each destination country offers. The uniqueness of the flow of traveler spending lies in the attractiveness of travel destinations, which is a factor beyond trade costs typically considered in the model of trade in goods. To explore the interaction between these two factors—trade costs and destination attractiveness—in international travelers' spending, we exploit political conflicts between the destination country and China as exogenous shocks to consumer preferences toward destination countries. We expect that a more hostile sentiment toward a particular destination

[33]Conversely, we find negative coefficients on the imports of mineral fuels/lubricants and machinery/transport equipment, although the coefficients are insignificant. These products are bulky and often transported by sea.

[34]According to Harrigan (2010), 65% of medical and pharmaceutical products are imported by air to the US in 2003.

Figure 6: Estimated Coefficients on Consumer Goods Imports by Industries




Notes: This figure shows the coefficients estimated by regressions of imports on air connectivity. We run regressions for different sub-industry categories of consumer goods imports from 2011 to 2016. Live animals are excluded from the food/beverages/tobacco industry.

may attenuate the effect of air connectivity on cross-border travel, while not significantly affecting the effect of air connectivity on trade in goods.

During our data period, there are four notable conflicts between China and Japan, the Philippines, South Korea, and Norway.[35] First, there was a political conflict over the Diaoyu Islands (also known as the Senkaku Islands) between China and Japan in 2012, which resulted in a series of anti-Japanese demonstrations, including consumer boycotts of Japanese products across many Chinese cities. Second, China and the Philippines had increasing tension over Huangyan Island (Scarborough Shoal) in 2012. As a result, China released a document to strengthen the inspection and quarantine of fruits imported from the Philippines. Third, in 2016, the South Korean and U.S. governments announced that they had agreed to deploy the Terminal High-Altitude Area Defense (THAAD) in the Korean peninsula.[36] China opposed the plan and imposed sanctions on travel and trade with South Korea. Fourth,

[35] Recent studies show an adverse effect of political conflict on trade between China and Japan (Heilmann 2016), Philippine (Luo et al. 2021), South Korea (Kim and Lee 2021), and Norway (Kolstad 2020).

[36] It is a defense system designed to shoot down ballistic missiles, which can be used as a defensive measure against North Korea's nuclear and missile threat.

Table 7: Air Connectivity and Boycotts

| | Card transactions | Consumer Goods imports | | |
|---|---|---|---|---|
| | | All | Food | Pharma & Cosmetics |
| | (1) | (2) | (3) | (4) |
| Weekly Frequency | 2.150*** | 0.130 | 1.083*** | 0.814*** |
| | (0.533) | (0.362) | (0.318) | (0.269) |
| Weekly Frequency × Boycotts | −0.241*** | 0.000 | −0.042 | 0.059 |
| | (0.058) | (0.038) | (0.035) | (0.038) |
| Origin city-year FEs | Yes | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes | Yes |
| Observations | 59,154 | 59,154 | 59,154 | 59,154 |

Notes: This table presents the results of IV regressions examining the impact of political conflicts on the effect of air connectivity. We use the value of card transactions as the dependent variable in column 1, and the value of consumer goods imports in column 2. In column 3, we specifically focus on consumer goods in the food, beverages, and tobacco industries, while in column 4, we use the value of consumer goods imports in the pharmaceutical and cosmetics industries. The first-stage F statistic is 21.72. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the Norwegian Nobel Committee awarded the Nobel Peace Prize to Chinese human rights activist, Liu Xiaobo. The award was announced in October 2010 and awarded in December 2010. The Chinese government strongly denounced the award and introduced political and economic sanctions against Norway.

We study the effect of these four political conflicts on Chinese traveler spending and imports of goods. First, we create an indicator of boycotts, $\mathcal{I}[Boycott_{jt}]$, that takes one for a country under the conflict in the year of each event. Specifically, the indicator equals one for Japan in 2012, one for the Philippines in 2012, one for South Korea in 2016, and one for Norway in 2011.[37] We then add the interaction term between the weekly frequency of direct flights ($\tilde{D}_{ijt}$ in equations 7 and 8) and $\mathcal{I}[Boycott_{jt}]$ to the 2SLS specification introduced in Section 3.4.[38]

[37]There are no direct flight schedules from Chinese cities to Norway during our data period. Travelers from China to Nordic countries often start trips from Finland (link; accessed on January 23, 2023). We use air flights to Finland instead.

[38]We do not include the indicator variable, $\mathcal{I}[Boycott_{jt}]$, in the regression because it will be absorbed by the country-year FEs.

The results are presented in Table 7. We find a negative and significant coefficient on the interaction term between air connectivity and boycotts (column 1). This result indicates that during a political conflict between China and a destination country, the positive effect of air connectivity on traveler spending decreases by 0.24% relative to the case without any conflicts. Interestingly, the coefficient on the interaction term is not statistically significant in the regression using the imports of consumer goods (columns 2). We continue to see statistically insignificant results when considering only imported consumer goods in the food/beverages and pharmaceuticals/cosmetics industries. These industries experience an increase in the value of imports due to the development of air connectivity. However, the political conflicts do not affect the positive impact of air transportation development in these two industries. Overall, our findings suggest that a rise in political conflicts—an adverse shock to consumer preferences—can offset the promoting effect of air connectivity on cross-border travel but not on trade in goods.

# 6 Conclusion

This paper investigates the impact of air connectivity on the spending of international travelers using unique data on card transactions from Chinese cities to foreign countries. We develop a novel instrument for air connectivity, focusing on the destination's comparative advantage in air transportation. Our result suggests that a 1% increase in the weekly frequency of direct flights between a Chinese city and a foreign country results in a 1.97% rise in the value of transactions in the destination country. We also evaluate a recent investment in air transportation infrastructure using the Istanbul Airport opening as an example. Our analysis suggests that there is a sizable benefit from inbound visitor spending compared with the cost of investment.

We extend our analysis to examine the effect of air connectivity on trade in goods. The results indicate that the enhancement of air transportation networks raises the value of imports of goods that are mostly transported by air, such as food/beverages and pharmaceuticals/cosmetics. Additionally, using political conflicts as exogenous shocks, we show that preferences toward travel destinations significantly influence the flow of traveler spending, but not the flow of goods trade.

Our study provides insight into the relationship between investment in air connectivity—through improvements in airports, for example—and traveler spending, which could inform policies meant to promote countries as attractive destinations. To precisely gauge the effect of investment in air connectivity on cross-border travel, policymakers need to be aware of the mediating role of local consumer preferences, such as cultural ties and sentiments toward destinations. Our results suggest that encouraging cultural exchanges with and creating welcoming sentiments toward inbound travelers are useful to boost the impact of air connectivity on international travel.

# Reference


Alderighi, Marco, and Alberto A. Gaggero. “Fly and trade: Evidence from the Italian manufacturing industry.” *Economics of transportation* 9 (2017): 51-60.

Allen, Treb, Simon Fuchs, Sharat Ganapati, Alberto Graziano, Rocio Madera, and Judit Montoriol-Garriga. “Urban welfare: Tourism in Barcelona.” Working paper (2023).

Anderson, Simon P., Andre De Palma, and Jacques-Francois Thisse. *Discrete choice theory of product differentiation*. MIT press, 1992.

Asplund, Marcus, Richard Friberg, and Fredrik Wilander. “Demand and distance: Evidence on cross-border shopping.” *Journal of public Economics* 91, no. 1-2 (2007): 141-157.

Autor, David H., David Dorn, and Gordon H. Hanson. “The China syndrome: Local labor market effects of import competition in the United States.” *American economic review* 103, no. 6 (2013): 2121-2168.

Baggs, Jen, Loretta Fung, and Beverly Lapham. “Exchange rates, cross-border travel, and retailers: Theory and empirics.” *Journal of International Economics* 115 (2018): 59-79.

BEA (US Bureau of Economic Analysis) “U.S. Travel and Tourism Satellite Account for 2017–2021.” *Survey of Current Business* (2023).

Bellemare, Marc F., and Casey J. Wichman. “Elasticities and the inverse hyperbolic sine transformation.” *Oxford Bulletin of Economics and Statistics* 82, no. 1 (2020): 50-61.

Campante, Filipe, and David Yanagizawa-Drott. “Long-range growth: economic development in the global network of air links.” *The Quarterly Journal of Economics* 133, no. 3 (2018): 1395-1458.

Chandra, Ambarish, Keith Head, and Mariano Tappata. “The economics of cross-border travel.” *Review of Economics and Statistics* 96, no. 4 (2014): 648-661.

Cristea, Anca D. “Buyer-seller relationships in international trade: Evidence from US States’ exports and business-class travel.” *Journal of international economics* 84, no. 2 (2011): 207-220.

Cristea, Anca D. “The role of aviation networks for urban development.” *Journal of Regional Science* (2023): 1–34.

Djankov, Simeon, Caroline Freund, and Cong S. Pham. “Trading on time.” *The review* *of Economics and Statistics* 92, no. 1 (2010): 166-173.

Faber, Benjamin, and Cecile Gaubert. "Tourism and economic development: Evidence from Mexico's coastline." *American Economic Review* 109, no. 6 (2019): 2245-2293.

Fageda, Xavier. "International air travel and FDI flows: Evidence from Barcelona." *Journal of Regional Science* 57, no. 5 (2017): 858-883.

Friberg, Richard, Frode Steen, and Simen A. Ulsaker. "Hump-shaped cross-price effects and the extensive margin in cross-border shopping." *American Economic Journal: Microeconomics* 14, no. 2 (2022): 408-438.

Gibbons, Stephen, and Wenjie Wu. "Airports, access and local economic performance: Evidence from China." *Journal of Economic Geography* 20, no. 4 (2020): 903-937.

Harrigan, James. "Airplanes and comparative advantage." *Journal of International Economics* 82, no. 2 (2010): 181-194.

Head, Keith, Thierry Mayer, and John Ries. "How remote is the offshoring threat?." *European Economic Review* 53, no. 4 (2009): 429-444.

Heilmann, Kilian. "Does political conflict hurt trade? Evidence from consumer boycotts." *Journal of International Economics* 99 (2016): 179-191.

Hovhannisyan, Nune, and Wolfgang Keller. "International business travel: an engine of innovation?." *Journal of Economic Growth* 20 (2015): 75-104.

Kim, Hyejin, and Jungmin Lee. "The Economic Costs of Diplomatic Conflict: Evidence from the South Korea–China THAAD Dispute." *Korean Economic Review* 37, no. 2 (2021): 225-262.

Kolstad, Ivar. "Too big to fault? Effects of the 2010 Nobel Peace Prize on Norwegian exports to China and foreign policy." *International Political Science Review* 41, no. 2 (2020): 207-223.

Luo, Changyuan, Shiyi Sun, and Guanghua Wan. "The impact of political relations on international trade: China–Philippines island dispute as a quasi-natural experiment." *The World Economy* 44, no. 11 (2021): 3422-3441.

Nocito, Samuel, Marcello Sartarelli, and Francesco Sobbrio. "A beam of light: Media, tourism and economic development." *Journal of Urban Economics* 137 (2023): 103575.

Organisation for Economic Co-operation and Development (OECD). "OECD Tourism

Trends and Policies 2020." (2020).

Söderlund, Bengt. "The importance of business travel for trade: Evidence from the liberalization of the Soviet airspace." *Journal of International Economics* 145 (2023): 103812.

Tanaka, Kiyoyasu. "Do international flights promote FDI? The role of face-to-face communication." *Review of International Economics* 27, no. 5 (2019): 1609-1632.

United Nations World Tourism Organization (UNWTO). "International Tourism Highlights, 2020 Edition." (2021).

Wang, Feicheng, Zheng Wang, and Zhuo Zhou. "All Roads Lead to Rome: Global Air Connectivity and Bilateral Trade." (2023).

Zhang, Chi, Ivan T. Kandilov, and Mark D. Walker. "Direct flights and cross-border mergers & acquisitions." *Journal of Corporate Finance* 70 (2021): 102063.

# Appendix A Appendix Tables

## A.1 Destination Countries

There are 71 unique foreign countries in our final dataset. The travel destinations in the data are mainly the countries of the Belt and Road Initiative in Eurasia, Japan, and EU countries.

Table A.1: Destination Countries

| | | | |
|---|---|---|---|
| Afghanistan | Austria | Azerbaijan | Bahrain |
| Bangladesh | Belarus | Belgium | Brunei |
| Bulgaria | Cambodia | Czech Rep | Denmark |
| Egypt | Estonia | Finland | France |
| Georgia | Germany | Greece | Hungary |
| Iceland | India | Indonesia | Iraq |
| Ireland | Israel | Italy | Japan |
| Jordan | Kazakhstan | Kuwait | Kyrgyzstan |
| Laos, PDR | Latvia | Lebanon | Luxembourg |
| Malaysia | Maldives | Malta | Monaco |
| Mongolia | Myanmar | Nepal | Netherlands |
| Norway | Oman | Pakistan | Philippines |
| Poland | Portugal | Qatar | Romania |
| Russian Federation | Saudi Arabia | Singapore | Slovakia |
| Slovenia | South Korea | Spain | Sri Lanka |
| Sweden | Switzerland | Tajikistan | Taiwan |
| Thailand | Timor-leste | Turkey | United Arab Emirates |
| United Kingdom | Uzbekistan | Vietnam | |

Note: The table lists the travel destinations in our data. See Section 2.1 for details.

## A.2 City-Country Pairs With the Largest Value of Transactions

The two biggest Chinese cities, Beijing and Shanghai, have the largest numbers of direct flights and the highest value of card transactions. One of our concerns is that the values of transactions were concentrated so much between these two cities and a particular foreign destination. Table A.2 shows the Chinese city-foreign country pairs with the five largest mean transaction values. The largest flows originated from the largest Chinese city (i.e., Shanghai and Beijing) to the largest economies with closer proximity (i.e., Japan, South Korea, and Taiwan). However, the shares of the values in these city-country pairs are very small. For example, the flow from Shanghai to Japan accounts for 4.9% on average. This implies that the transaction values are not concentrated in a handful of city-country pairs.

Table A.2: City-Country Pairs With the Five Largest Transactions

| City | Country | Average (yearly) | Share |
|---|---|---|---|
| Value of transactions (in million RMB): | | | |
| Shanghai | Japan | 4,969.72 | 0.049 |
| Shanghai | South Korea | 3,113.90 | 0.031 |
| Beijing | Japan | 3,087.32 | 0.030 |
| Beijing | South Korea | 2,925.83 | 0.029 |
| Shanghai | Taiwan | 2,264.65 | 0.022 |

Note: This table shows the Chinese city-foreign country pairs with the five largest average transaction values. The average value of transactions is calculated for each city-country pair over the sample period. The shares are the average values (at the city-country level) over the total value. The total average value is 101,407.3 million RMB.

## A.3 Air Connectivity in 2011 and 2016

One of the components of our IV is the global share of the number of flights departing a foreign country. In Table A.3, we list the countries with the most significant change in total outbound flights between 2011 and 2016. The countries with larger growth in the number of outbound flights contribute to the variation in our IV.

Table A.3: Number of Total Outbound Flights in 2011 and 2016

| Country | 2011 | 2016 | Change | Percentage Change |
|---|---|---|---|---|
| United Arab Emirates | 204,239 | 311,963 | 107,724 | 52.7% |
| United Kingdom | 652,308 | 757,293 | 104,985 | 16.1% |
| Turkey | 152,501 | 242,752 | 90,251 | 59.2% |
| Spain | 421,287 | 498,736 | 77,449 | 18.4% |
| Saudi Arabia | 81,558 | 148,373 | 66,815 | 81.9% |
| Japan | 121,180 | 183,392 | 62,212 | 51.3% |
| South Korea | 86,861 | 135,877 | 49,016 | 56.4% |
| Qatar | 65,012 | 110,774 | 45,762 | 70.4% |
| Thailand | 105,348 | 149,051 | 43,703 | 41.5% |
| Taiwan | 66,535 | 105,451 | 38,916 | 58.5% |
| India | 124,020 | 161,777 | 37,757 | 30.4% |
| Italy | 353,339 | 390,640 | 37,301 | 10.6% |
| Netherlands | 210,521 | 247,306 | 36,785 | 17.5% |
| Greece | 77,035 | 108,384 | 31,349 | 40.7% |
| Malaysia | 101,772 | 132,454 | 30,682 | 30.1% |
| Poland | 87,968 | 118,135 | 30,167 | 34.3% |
| Germany | 649,054 | 678,885 | 29,831 | 4.6% |
| Portugal | 99,329 | 126,971 | 27,642 | 27.8% |
| Ireland | 92,931 | 119,556 | 26,625 | 28.7% |
| France | 457,523 | 483,516 | 25,993 | 5.7% |

Note: This table lists 20 countries with the largest change in the number of outbound flights from 2011 to 2016. The second and third columns report the number of total outbound flights (excluding China) from the countries in 2011 and 2016, respectively. The fourth column shows the change in total outbound flights (excluding China) from 2011 to 2016. The last column reports the percentage change in outbound flights in each country.

# Appendix B Data Appendix

## B.1 Card Transaction Data

- Chinese cities

  - Chinese cities in our data are four centrally administered municipalities (Beijing, Tianjin, Chongqing, and Shanghai) and the prefecture-level cities, including 292 prefecture-level cities, seven regions, 30 autonomous prefectures, and three leagues (see the Administrative Divisions of the People's Republic of China link for the details). Two prefecture-level cities, Sansha City and Danzhou City, are not in our transaction data. In total, our dataset comprises 336 Chinese cities, including 193 with airports.

- Data in 2016

  - We address the missing data from September to December 2016 using the monthly transaction data in 2015. This approach allows us to consider the seasonality of travel demands across different regions. The monthly transaction data are aggregated at the China-foreign country level (unlike the yearly data, the monthly data are not disaggregated by Chinese city).

  - Because few monthly transactions are recorded in some foreign countries, we aggregate countries into sub-regions based on the geographic regions defined by the United Nations (link). For each sub-region, we calculate the share of transaction values made from January to August relative to the total value. On average, the share is 66%. A higher proportion of travelers visit Western Europe between January and August (around 70% of the total transactions in 2015) compared to Southern Asia and Eastern Europe. Specifically, we calculate for each sub-region:

$$Expected[x_{t=Jan-Dec,\ 2016}] = x_{t=Jan-Aug,\ 2016} \times \frac{x_{t=Jan-Dec,\ 2015}}{x_{t=Jan-Aug,\ 2015}},$$

  where $x_t$ is the value of transactions over the period, $t$.

  - Egypt is the only Northern African country in our data, so we added it to the Western Asian region (which includes Saudi Arabia).

## B.2 Global Flight Schedules

- OAG Analyzer
  - We restrict the data to passenger flights (excluding cargo flights) and flights operated by operating carriers (excluding code-share flights).
  - The data is at the air-carrier level. We use only the flights run by operating carriers and exclude code-share flights.
  - We consider all flights arriving in destination countries, regardless of the cities of arriving airports.
  - We add names of the cities with airports to the original data using the table provided by OAG. We also searched on the internet to identify airports serving two cities. The following airports serve two cities: Yangzhou Taizhou International Airport (serving Taizhou and Yangzhou), Xining Caojiabao International Airport (serving Haidong and Xining), Xi'an Xianyang International Airport (serving Xianyang and Xi'an), and Lhasa Kongga International Airport (serving Shannan and Lhasa).
  - OAG records flights with stopovers, not just direct flights. For flights with stopovers at domestic airports before departing for foreign countries, we keep only the flights bound for foreign countries. For example, a flight route from Chongqing to Japan connects through Shanghai. We focus on direct flights connecting a Chinese city with a foreign country (e.g., flights from Shanghai to Japan) and exclude domestic stopover flights (e.g., flights from Chongqing to Japan).
  - Regarding flights with stopovers at international airports, we use only the flights directly connecting Chinese cities with foreign countries. For example, there is a stopover flight departing from Guangzhou to Sri Lanka via Thailand. We keep only the flight from Guangzhou to Thailand.

- Weekly frequency of direct flights
  - We calculate the sum of frequencies in each Chinese city-destination country-year and divide the total by 52 to measure the weekly frequency.
- Travel time (for Section 4.2.2)
  - We identify the most frequent flight routes to destination countries. For example, flights from Beijing to Japan arrive at different airports such as Narita, Haneda, Osaka, New Chitose (located in Hokkaido), and Naha (located in Okinawa). We use the travel time of the flight between Beijing and Narita because flights to Narita are the most frequent from Beijing.
  - There are some extremely short elapsed times in the data. We exclude the route if the data suggest that a plane travels at speeds exceeding 1,000 km/hour.
  - Even on the same flight route, the elapsed time can vary slightly in different flight schedules. We calculate the average flight time using the frequency of flights as the weight. This allows us to have the same elapsed time on the same flight routes over the data period.
  - After cleaning the data, we consider all possible flight routes with up to three stops (two stops at domestic airports and one stop at a foreign airport). We add a three-hour layover time for every stop to the total elapsed time. We then select the route with the shortest travel time among all of the possible flight routes.
  - We keep city-country pairs with travel time recorded over our data period.