# The Impact of Air Connectivity on Travel and Goods: Evidence from Cross-border Card Payments*

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**Abstract**

We study the impact of air connectivity on trade in travel services, the biggest tradable service sector. A novel dataset on on-site card payments made by Chinese travelers allows us to investigate the effects of air connectivity on the bilateral flow of travel services. We instrument for Chinese city-level air connectivity using a measure of destination countries' comparative advantage in air transportation. Our IV estimates indicate that a 1% increase in the weekly frequency of direct flights leads to a 1.8% increase in cross-border card transaction value. While air connections promote cross-border trade in travel services, we find that negative shocks to consumer tastes can diminish this effect. By contrast, such changes in consumer preferences have no effect on the trade in goods. This research sheds light on the role of air connectivity in shaping trade in travel services and its interaction with consumer preferences.

Keywords: Cross-Border Travel, Bilateral Trade, Air Transportation, and Trade Cost
JEL Classification: F10, F14

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# 1 Introduction

Travel services such as tourism and business trips account for a plurality of overall traded services and contribute substantially to the global economy.[1] Consumers enjoy products and services that are not available in the domestic market in foreign destinations, which is the source of the welfare gains from trade in travel services (e.g., the love-of-variety model). The enhancement of air connectivity, leading to a decline in travel costs, has the potential to incentivize more consumers to travel abroad (i.e., more consumers to import travel services) and ultimately enhance consumer welfare. To measure the welfare gains from trade, one crucial factor is the trade elasticity, which represents the sensitivity of the value of imports to changes in trade costs (Arkolakis et al. 2012). An extensive literature analyzes trade elasticity in goods imports and contributes to policymaking as it helps measure the impact of new trade agreements and infrastructure development on consumer welfare. However, limited research has provided evidence on the extent to which air connectivity promotes international travel. The scarcity of data on travel service trade hinders policymakers from accurately quantifying the welfare effects of air connectivity improvements.

Addressing this gap, this paper presents the first attempt to examine the effect of air connectivity on trade in travel services. We collect a novel dataset containing aggregated Chinese consumer card transactions made in foreign countries. In particular, we observe how much is spent and how many transactions are made by consumers from a given Chinese city (hereafter, origin city) in a given foreign country (hereafter, destination country). We combine these transaction data with data on all flights between Chinese cities and foreign countries, which allows us to measure air connectivity between two locations with the frequency of direct flights between them. We construct a yearly origin city-destination country panel spanning 2011-16.

We develop a model to explain the bilateral flow of travel service trade, following Farber and Gaubert (2019) and Head et al. (2008). 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). To identify the effects of air connectivity

[1] Trade in services has been expanding rapidly, accounting for 25% of global trade in 2019. The share of trade in travel service is around 25% in the total service trade. (UNCTAD 2021).

on travel service trade, we leverage the variation in air connectivity over time within a specific Chinese city-foreign country pair.

A 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 the share of global flights arriving in the destination country (representing that country's comparative advantage in air transportation) combined with the distance between a Chinese city-foreign country pair (representing trade costs between these markets). The identifying assumption is that the share of the flights coming to a country is uncorrelated with demand shocks in a particular Chinese city for travel to that country. Our IV is analogous to that of Autor et al. (2013), who use cross-industry and across-time variation in Chinese comparative advantage and trade costs to instrument for Chinese import exposure in the US.

Our IV estimates indicate that a 1% increase in the weekly frequency of direct flights between a city-country pair can lead to a 1.8% increase in the value of card transactions in the destination country. This result is robust to different specifications and sample restrictions. Further, we use the political conflict against Japan in 2012 as an exogenous variation for a robustness check. This alternative identification strategy also shows that the improvement of air connectivity leads to an increase in the card transaction value.

Improvement in air connectivity not only impacts travel service trade but also exerts an influence on trade in goods. For instance, passenger planes transport air freight, and consumers who experience new products in their travel abroad may develop a preference for those items, leading to increased imports. Building on this premise, we further analyze how improvements in air connectivity affect Chinese imports using customs data. 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 an important factor in consumers' travel decisions. Such destination characteristic is unique for travel service trade, but not for trade in goods. To explore this model's implications, we look at how consumer tastes and preferences toward foreign countries (i.e., one example of the destinations' attractiveness) affect our findings by exploiting political conflicts as exogenous adverse shocks. We find that negative sentiment towards foreign counties 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, we do not observe analogous effects of shifts in public opinion on the trade in goods. This suggests that the impact of air connectivity on travel service trade is influenced by consumer preferences towards specific destinations, while trade in goods may not be as sensitive to such sentiments.

China presents a useful case study for understanding the relationship between air connectivity and trade in travel services. Cross-border travel is an important and growing market in China. The Chinese aviation network has dramatically developed, and China has been the world's second-largest air transportation market since 2013 (Gibbons and Wu 2020). For example, the total number of outbound tourists increased from 34.5 million in 2006 to 122 million in 2016, and the number of foreign countries connected with Chinese cities by air increased by around 70% from 2000 to 2016.[2,3] These rapid expansions of cross-border travel and air connectivity provide meaningful variation for our estimation.

This paper contributes to a growing body of empirical work that looks at 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. 2021; Söderlund 2022), foreign investment (Campante and Yanagizawa-Drott 2017; Fageda 2017; Tanaka 2019), and cross-border mergers and acquisitions (Zhang et al. 2021). Our work extends the literature by looking into the effects of international air transportation on trade in services and goods in a unified setting.

Our study is also related to the literature on cross-border travel, which identifies various determinants for consumers traveling to shop in another country. Asplund et al. (2007) and Friberg et al. (2022) use data of Sweden and Denmark, while Chandra et al. (2014) and Baggs

[2]The number of outbound tourists is from the *China Tourism Statistics Bulletin* published by the National Tourism Administration from 2006 to 2015, and *Big Data on Chinese Outbound Tourists* jointly issued by the China Tourism Academy and Ctrip in 2016.

[3]According to the *Statistical Data on Civil Aviation of China 2017*, the number of foreign countries connected with Chinese cities by air is 33 in 2000 and 56 in 2016. The number of Chinese cities with airports doubled, from 126 cities in 2000 to 214 cities in 2016.

et al. (2018) look into cross-border travel between Canada and the US.[4] Unlike these papers, we study cross-border travel between non-contiguous countries, which has been becoming more common as air transportation becomes more affordable.

The outline of the paper is as follows. We introduce data and stylized facts in Section 2 and the model in Section 3. Section 4 presents the empirical strategy. We report the main results with cross-border card transaction data in Section 5. Section 6 shows further analyses using customs data. Section 7 concludes.

# 2 Data and Stylized Facts

We use a unique dataset of Chinese card transactions made in foreign countries. We merge the card transaction data with worldwide international flight schedules to examine the impact of air connectivity on Chinese overseas travel spending. We also use supplementary data sources, including Chinese customs data and the number of casualties during the Second Sino-Japanese War. Our novel data show that China has experienced the evolution of air transport networks between Chinese cities and foreign countries, and this air transportation development is positively correlated with the value of cross-border 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. The data include transactions made by Chinese cardholders outside China, excluding online transactions.[5] For each transaction, we observe

[4] These papers show that travel costs (proxied by distance) and price differential drive cross-border travel. For example, Chandra et al. (2014) find that a stronger Canadian dollar against the US dollar (proxies for a lower foreign price for Canadians) motivates cross-border travel, and the responses of cross-border travel to currency fluctuations are mitigated by distance to the border. Baggs et al. (2018) show similar results for consumers as Chandra et al. (2014) but also show results on how the cross-border travel of Canadians to the US hurts Canadian retailers.

[5] Our data contain the transactions made through domestic payment cards, but not foreign payment cards such as Visa and Mastercard. This limitation does not obviously bias our analyses because most Chinese residents use domestic payment cards. (reference: *Payment methods report 2019* on page 21, link to the report (last access on November 6, 2022))

the cardholder's city of residence, the country where the transaction was made, and the time and value of the transaction.[6] The travel destinations in the data are the countries of the Belt and Road Initiative in Eurasia, Japan, and EU countries.[7] For confidentiality purposes, our data provider aggregates the data at the year-city of residence-destination country level.

**(ii) Worldwide flight schedules**

The air connectivity data comes from OAG Analyser, which provides worldwide flight schedules. This dataset includes information such as 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 using the correspondence tables provided by OAG.[8]

Our primary measure of air connectivity is the weekly frequency of direct flights between a Chinese city and a destination country.[9] We also employ travel time from a Chinese city to a foreign country as an alternative measure of air connectivity. In case no international direct flights are available from a particular city, we consider the time for domestic flights from that city to the nearest airports offering international direct flights and add an additional three hours of layover time. We exclude cities without direct domestic flights to the nearest airports.

**(iii) Chinese import data**

Chinese import data are collected by China's General Administration of Customs (CGAC) for the period of 2011-2016. For each import transaction, we observe the company name,

[6]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.

[7]A list of countries within the Belt and Road Initiative can be found here (last accessed on November 6, 2022). Egypt is not in Eurasia but is included in the list. Lithuania is a member of the EU, and Yemen is in Eurasia, but they are not on the list.

[8]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).

[9]Some flights have one or two stopovers at domestic airports before departing for foreign countries. For example, a flight route from Chongqing to Japan connects through Shanghai. We focus solely on direct flights connecting a Chinese city with a foreign country (e.g., flights from Shanghai to Japan), and therefore we exclude domestic stopover flights (e.g., flights from Chongqing to Japan).

company code, city of the company's location, product name, product code (at the HS 8-digit level), country of origin, time (year and month), and transaction value.[10] Our data also categorize transactions into ordinary trade and non-ordinary trade (such as processing trade).

**(iv) Number of casualties during the Second Sino-Japanese War**

The number of casualties during the Second Sino-Japanese War comes from Chi (1987).[11] This source provides information on the number of individuals who suffered minor or major injuries, as well as those who lost their lives during the war, at the provincial level. We estimate the number of casualties at the city level, using the share of the pre-war city population in the total province-level population.[12] The city population data for 1934 is obtained from the China City and County Land and Population Census.[13]

## 2.2 Descriptive Statistics

We merge the two main datasets, the Chinese card transaction data and the flight data. The final dataset includes 192 unique Chinese cities (origins) and 72 unique foreign countries (destinations), resulting in a total of 58,932 origin-destination pairs.[14] The destination countries are listed in Table A.1.

Table 1 presents the descriptive statistics of our estimation sample. We measure the size of overseas card transactions using the total value of transactions as well as the total number of transactions. On average, Chinese travelers spend 9.3 million Renminbi (RMB) and conduct around 5,000 card transactions in foreign counties per year. The distributions of the value and the number of transactions are skewed to the right since the mean value is larger than the median value. Similar to the transaction value and number, the distribution

[10] 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.

[11] The data are publically available (link).

[12] We do not observe both the number of population and the number of casualties for some cities in our data sample. We assume that there were no casualties in those cities during the war.

[13] The Department of the Interior, Statistical Division published this dataset in the year 1935. In this dataset, we observe the province name, city name, and population.

[14] We focus on the cities 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. Additionally, countries without airports (The State of Palestine, Liechtenstein, and Vatican City State) cannot be matched with flight data.

of the weekly frequency is right-skewed, likely because some cities have larger airports that attract more direct flights. On average, each origin city-destination country pair has 0.45 weekly flights.

## 2.3 Stylized Facts

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

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

Figure 1 shows the value of transactions on a map of mainland China, highlighting the variation across cities. We observe that some cities have experienced substantial increases in transaction value, while others have not. Interestingly, the large growth of the transaction values can be observed not only in the cities in Eastern China but also in inland regions. For example, the total overseas transactions in Wuhan (an inland city in Hubei Province) have increased by around 421%, from 441 million to more than 2 billion RMB.

We also observe the difference in the change in the transaction value across destination countries. Japan is the country that receives the largest amount of card transactions (Figure 2). The total flow from China to Japan amounted to around 2.6 billion RMB in 2011 and soared to around 29 billion RMB in 2016. Countries further from China also experienced sizeable growth in transactions. For example, around 7 billion RMB in transactions occurred in France through on-site card payments in 2016.

**Fact 2: Increased connectivity of Chinese cities through direct flights**

Figure 3 shows the distributions of the numbers of international direct flights across Chinese cities in 2011 (Panel (a)) and 2016 (Panel (b)). We observe a higher frequency (greater heights with most of the bars) in 2016 than in 2011, which implies more cities have international direct flights in 2016.

The world map with international flight routes gives us a clear picture of the improvement in Chinese aviation networks. Figure 4 reveals that there were more direct flight routes connecting Chinese cities with foreign countries in 2016 (Panel (b)) than in 2011 (Panel (a)).

Several inland cities, including Lijiang and Yichang, got new direct flights to overseas destinations. In fact, 24 cities did not have direct flights to any foreign countries in 2011 but got direct flight connections by 2016.

**Fact 3: Positive relationship between air connectivity and card transaction values** Figure 5 indicates a positive correlation between the value of card transactions (y-axis) and the number of direct flights among Chinese cities (x-axis). In Panel (a), we observe that major cities such as Shanghai, Beijing, and Guangzhou have a larger number of direct flights (e.g., more than 500 direct flights per week) compared to other Chinese cities. Even when focusing on the other Chinese cities with fewer than 500 direct flights (Panel (b)), a positive relationship between the weekly frequency of direct flights and card transaction values is evident. In the subsequent sections, we empirically investigate these positive relationships.[15]

# 3 Model

We develop a model to explain the flow of tourism and travel-related services from Chinese cities to foreign countries (i.e., Chinese imports of tourism and travel-related services from foreign countries). The model is based on Eaton and Kortum (2002). Each foreign country offers amenities for travelers, and a consumer makes a discrete choice among her possible destinations based on her preferences. We refer to Farber and Gaubert (2019) to set up consumers' utility for tourism and travel-related services. We also rely on Head et al. (2008) who introduce a model for bilateral service trade to derive a gravity-type equation for trade in the travel service sector.

[15] Omitting the top origin-destination pairs does not affect our descriptive results (see Table A.2). Put differently, our findings are not driven by the extensive travel between Beijing and Shanghai and nearby countries (Japan and South Korea).

## 3.1 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 in 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 $X_i = \beta_i Y_i$ for their travel services. $Y_i$ is the aggregate income of a Chinese city, $i$. Given this budget for travel, a consumer decides her destination and travels there to consume tourism-related services.

A consumer in city $i$ receives the following utility when she visits 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 $\tau_{ij}$ 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 service in the destination, $j$. We restate the utility from travel:

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

## 3.2 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 tourism 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, De Palma, and Thisse (1992, p.39), the choice probability takes the multinomial logit formula[16]:

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

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, $p_j$.

[16] 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

### 3.3 Bilateral Flow of Travel Service Trade

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

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

where $X_i$ is the aggregate expenses on travel service trade 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 travel service flow 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 $\Phi_{it} = \left[ \sum_{j=1}^{J} N_{jt} \left( \frac{\tau_{ijt} p_{jt}}{A_{jt} \beta_{it} Y_{it}} \right)^{-\theta} \right]^{-\frac{1}{\theta}}$.

### 3.4 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 cultural relationships. 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 equation (2) and using equation (3), we obtain the equation that represents the log of the expected trade flow in travel services 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 travel service flow 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.

# 4 Empirical Strategy

## 4.1 Model Implementation: OLS Estimation

Equation (4) represents the expected 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 actual 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 flight, $D_{ijt}$. We apply the inverse hyperbolic sine (or arcsinh) transformation to both variables to address this issue. This transformation approximates the natural logarithm of the variables while allowing for zero observations.[17] The estimated coefficient can be approximated to the elasticity, which is the ratio between the percentage change in the transaction value and the corresponding percentage change in the weekly frequency of direct flights (Bellemare and Wichman 2022).[18]

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., number of weekly direct flights between $i$ and $j$). The inverse hyperbolic sine transformation has been applied to both variables. 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

[17] The formula for the inverse hyperbolic sine transformation is $\tilde{x} = arcsinh(x) = \ln(x + \sqrt{x^2+1})$.

[18] Alternatively, we could employ the Poisson Pseudo Maximum Likelihood (PPML) regression to address zero values. See footnote 25 for further details.

inward multilateral resistance and unobserved destination-specific time-variant factors, such as tourist attractions and the price of travel services.

We expect that new direct flights 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.

## 4.2 Endogeneity and IV Approach

Our goal is to identify the effect of flight 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 services 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.

### 4.2.1 Designing an Instrumental Variable

We introduce a Bartik-style instrumental variable (IV) to overcome this endogeneity concern. Our instrument exploits plausibly exogenous variation in air connectivity in 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 share of total global flights (excluding China) for which country $j$ is the destination ($\lambda_{jt} = \frac{flight_{jt}}{\sum_j flight_{jt}}$), and $dist_{ij}$ is the geographical distance between $i$ and $j$.[19] This IV is analogous to the one developed by Autor, Dorn, and Hanson (2013), who instrument for US imports from China using other countries' imports from China (i.e., China's comparative advantage in productivity) and trade costs. We instrument for Chinese air connectivity using other countries' air connectivity (i.e., their comparative advantage in air transportation

[19] We exclude the flights from China to construct the value, $\lambda_{jt}$.

technology) and trade costs (i.e., distance).

Our instrument is expected to be negatively correlated to the frequency of flights, $D_{ijt}$: a country with a comparative advantage in air connectivity is more likely to have direct flights, while city-country pairs that are further apart likely have fewer direct flights connecting them. The negative relationship between distance and air connectivity reflects the higher trade costs (in services) between more distant markets.[20] We assume that distance affects our dependent variable (value of card transactions) only through air connectivity (our endogenous variable).[21] Multiplying the distance between city $i$ and country $j$, $dist_{ij}$, by the country-time level share $\lambda_{jt}$, gives the city-country-year level variation for our instrumental variable.

### 4.2.2 Identification Assumption

Our key identifying assumption is that the share of the flights coming to a country $j$, $\lambda_{jt}$, is uncorrelated with demand shocks in a particular Chinese city for travel to a 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 characteristics of Chinese origin cities that might influence demand for travel services, except 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 (The United Arab Emirates 2017).[22] 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. Appendix A.4 shows the change in the number of inbound flights to the UAE between 2011 and 2016. The number of flights arriving in the UAE increased by 167%

[20] 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).

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

[22] Source: Statistical Yearbook of Abu Dhabi 2017, link to the article (last access on November 5, 2022)

during our data period. This and similar government efforts to attract direct flights depend on investment decisions by local governments, not shocks to travel demand in particular Chinese cities.

### 4.3 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 share of global flights arriving in 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 air connectivity between $i$ and $j$, $\xi$. 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 $j$.

## 5 Results: Trade in Travel Services

We estimate the impact of air connectivity on trade in travel services using our linked flight-Chinese card transaction data and our IV framework. We first report 2SLS results, using the equation we define in Section 4.3, that show how direct air routes affect trade in travel services. We then consider the robustness of our estimates to different specifications and definitions of air connectivity.

## 5.1 Main Results

In our main specification, we analyze the impact of the improvement in the weekly frequency of direct flights on card transaction values. Column 2 of Table 2 shows the 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 1.82% increase in cross-border travel spending. 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 24.57, which suggests that we can reject the null of a weak instrument.[23]

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 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 services. 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 services 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 columns 3 and 4, we limit and expand our sample size to check if the results differ substantially based on our sample selection. One potential issue is that most Chinese international travelers are from Shanghai and Beijing, and therefore our estimate may be largely

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

driven by the travelers from these two cities.[24] We drop 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 2 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 2) in terms of size, significance, and sign. These results suggest that our estimates are not specific to the two largest Chinese cities.

We also 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 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 4 of Table 2. 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 2) because it includes the variation of air connectivity due to an establishment of airports.

## 5.2 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 results (column 2 of Table 2) are robust using alternative measures of air connectivity and travel spending.[25] We also consider an alternative identification approach for causal inference.

[24] Table A.2 shows that 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).

[25] One of the possible robustness checks is conducting a Poisson Pseudo Maximum Likelihood (PPML) regression. The result from a Poisson Pseudo-Maximum-Likelihood (PPML) regression is similar to the one in our OLS result (column 1 of Table 2). However, when we apply PPML regression with our IV and fixed effects using the control function method, the coefficient of our interest loses significance. In the control function method, we initially regress our dependent variable, i.e., the value of transactions, on our IV, and then regress the error term generated from the first regression on the weekly frequency of direct flights. Running PPML regression using the control function method proves challenging in our case, as the three fixed effects absorb most of the endogeneity in the error term.

### 5.2.1 Alternative Variables

One of the robustness checks is to employ alternative specifications of our dependent variable. First, we replace the value of card transactions with the number of card transactions. Column 1 of Table 3 reports that a 1% increase in weekly direct flights leads to a 0.30% increase in the number of card transactions. The positive and statistically significant result is similar to the main result using the value of transactions.

We also take into account that Chinese travelers possibly use ground transportation and visit other countries following their international flights. This concern is especially relevant in European countries. To address this issue, we group European countries into four geographical regions and measure the frequency of direct flights for each European region.[26] Column 2 of Table 3 shows the result of this alternative regression, and the coefficient closely aligns with our main regression result.

In addition, we 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 an airport and consider flights departing from airports within a 200 km radius. In our main specification, Chinese travelers access only the international direct flights departing from their residing cities. However, in the alternative specification, travelers can benefit from additional international direct flights departing from nearby cities. The regression result supports this assumption—we observe a larger coefficient on the weekly frequency of direct flights (column 3 of Table 3).

### 5.2.2 A Quasi-Experiment for Causal Inference

We employ an alternative identification strategy that relies on a plausible quasi-natural experiment. Specifically, we exploit the political conflict on the Senkaku (Diaoyu) Islands between China and Japan in 2012 as an exogenous shock to the relationship between China and Japan. Heilmann (2016) finds that there was a disruption in imports from Japan to China as a result of the Senkaku conflict. Such conflict should also affect trade in travel services.

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

The degree of anti-Japanese sentiment varies across Chinese cities, and it relates to the impact caused by the Second Sino-Japanese War in 1937-44. We refer to Che et al. (2015) and use the number of casualties (the number of civilians who were injured or died due to the Japanese invasion in a region) as an exogenous city-level variation on the effect of the political conflict. The time variation of political shock and the city variation in causality allows us to use a model in the spirit of the difference-in-differences (DiD) approach. We expect consumers in the cities with a larger number of casualties will be more hostile to Japan and hence less likely to travel to Japan during the period of the political conflict. More significant anti-Japanese sentiment can reduce the air connectivity between a Chinese city and Japan. We use the city-level impact of the political conflict as an instrumental variable to our air connectivity measure (i.e., the weekly frequency of direct flights).

We define the alternative IV as follows:

$$V_{it} = Casualties_i \times Boycott_t,$$

where $Casualties_i$ is the number of casualties in city $i$ and $Boycott_t$ equals 1 in the year 2012, and 0 otherwise.[27] In our main specification (equation 7), we use this alternative IV, $V_{it}$, instead of the IV we previously used, $Z_{ijt}$. Here, since we consider Japan as the only destination country, the variation in our data is at the city-year level (i.e., destination $j = Japan$).

Column 4 of Table 3 shows the result with our new IV measure, $V_{it}$. The coefficient on the log of weekly frequency (our air connectivity measure) is negative and significant in the first stage of the regression. We find the positive and significant coefficient on the log of frequency in the second stage, which is consistent with our main results. This result indicates that a 1% increase in the weekly frequency of direct flights leads to a 0.94% increase in card transaction value made by Chinese travelers in Japan.

[27] We add one to the interactions term before taking logs to deal with zero values.

# 6 Further Analyses

We showed that the development of direct flight connections leads to an increase in cross-border card transaction values. We extend our analysis and look at the effect of air connectivity on trade in goods. We also study how shocks to consumer tastes and preferences toward destination countries affect our findings.

## 6.1 Trade in Goods

Improvement in air transportation networks affects not only consumer travel (that we measure by cross-border card transactions) but also trade in goods. One may assume that an increase in travel services would have a positive spillover effect on trade in goods, particularly in the context of consumer goods. Travelers experience new products in countries they visit and may start purchasing the products after their travels. Thus, more direct flight connections increase the number of travelers, which in turn leads to an increase in the value of imports from the countries with more frequent flight connections.[28] Moreover, some freight is shipped by passenger flights along with passengers and their baggage, although the amount of shipment is small compared to cargo flights.[29] A 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 upon this idea, we extend our analysis to estimate the effect of air connectivity on the import of goods from country $j$ to Chinese city $i$ by running the IV regression introduced in Section 4.3. Specifically, we use the value of import as a dependent variable instead of the card transaction value (i.e., $\tilde{X}_{ijt}$ in equation 8).

We begin our analysis by examining the impact of air connectivity on the value of total imports, but the coefficient does not show statistical significance (column 1 of Table 4). Therefore, we further explore the effect on the imports of consumer products, which are more relevant to consumption by travelers, in various industries. Specifically, we refer to

[28] Similarly, Söderlund (2022) shows that a decline in the costs of business travel (i.e., air travel time) increases trade volume using the liberalization of the Soviet airspace in 1985 as a natural experiment.

[29] 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 (reference: Alaska Air Forwarding link to the article, last access on January 21, 2023).

UNCTAD's categorization for consumer products and run regressions using the value of imported consumer products in each industry at the one-digit level of the SITC Revision 4.

While the coefficient on the regression with total consumer goods imports is not statistically significant (column 2 of Table 4), the results exhibit heterogeneity across different industries, as illustrated in Figure 6. Interestingly, we observe that the imports of food/beverage and pharmaceutical/cosmetic products increase by 1% with a 1% increase in the weekly frequency of direct flights.[30] It is worth noting that these products are mostly transported by air. For instance, food/beverage 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).[31]

## 6.2 Effects of Political Conflicts

Unlike trade in goods, our model considers that the utility of travelers depends not only on trade costs but also on the amenity that each destination country offers. The uniqueness of travel service trade lies in the attractiveness of travel destinations, which is a factor beyond trade costs typically considered in the model of goods trade. To explore the interaction between these two factors—trade costs and destinations' attractiveness—in travel service trade, we exploit political conflicts between the destination country and China as an exogenous shock to consumer preferences toward destination countries. We expect that a more hostile sentiment towards a particular destination may attenuate the effects of air connectivity on cross-border travel, while not significantly affecting the effects of air connectivity on trade in goods.

During the data period, there are four notable conflicts between China and Japan, the Philippines, South Korea, and Norway.[32] First, there was a political conflict over the Senkaku (Diaoyu) 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

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

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

[32] 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).

cities. Second, China and the Philippines had increasing tension over Huangyan Island 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.[33] China opposed the plan and imposed sanctions on travel and trade with South Korea. Fourth, 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 trade in travel services and imports of goods. First, we create an indicator of boycotts, $\mathcal{I}[Boycott_t]$, 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.[34] Second, we add the interaction term between the weekly frequency of direct flights ($\tilde{D}_{ijt}$ in equations 7 and 8) and $\mathcal{I}[Boycott_t]$ to the 2SLS specification introduced in Section 4.3.

The results are presented in Table 5. We find a negative and significant coefficient on the interaction term between air connectivity and boycott (column 1). This result indicates that the effect of air connectivity on travel service trade decreases when there is a political conflict between China and a destination country. Interestingly, the coefficient on the interaction term is not statistically significant concerning 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. Overall, the findings suggest that a rise in political conflicts—an adverse shock of consumer preferences towards destination countries—can offset the promoting effect of air connectivity on cross-border travel but not on trade in goods.

[33]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.

[34]There are no direct air flight schedules from Chinese cities to Norway during our data sample. It is common to start trips from Finland for travelers from China to Nordic countries (link, last access on January 23, 2023). We use air flights to Finland instead.

# 7 Conclusion

This paper investigates the impact of air connectivity on trade in travel services, leveraging unique data on card transactions from Chinese cities to foreign countries. Using a novel instrument for air connectivity based on the destination's comparative advantage in air transportation, the 2SLS estimate reveals that a 1% increase in the weekly frequency of direct flights between a Chinese city and a destination country results in a 1.8% rise in the value of on-site card payment in the newly connected country. Our results are robust to alternative definitions of variables and sample sizes.

Moreover, we extend our analyses to examine the effect of air connectivity on trade in goods. The result indicates that the enhancement of air transportation networks raises the value of imports of products that are mostly transported by air, such as food/beverages and pharmaceuticals/cosmetics. Additionally, using political conflicts as exogenous shocks, we show that the attractiveness of travel destinations significantly influences the flow of travel service trade, but not the bilateral flow of goods trade.

This study provides insight into the relationship between investment in air connectivity—via improvements in airports, for example—and trade in services and goods, which could inform policies meant to promote economic relationships with foreign countries. 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 towards destinations). Our results suggest that encouraging cultural exchanges with and creating welcoming sentiments towards foreign countries are useful to boost the impact of air connectivity on cross-border travel.

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# Figures

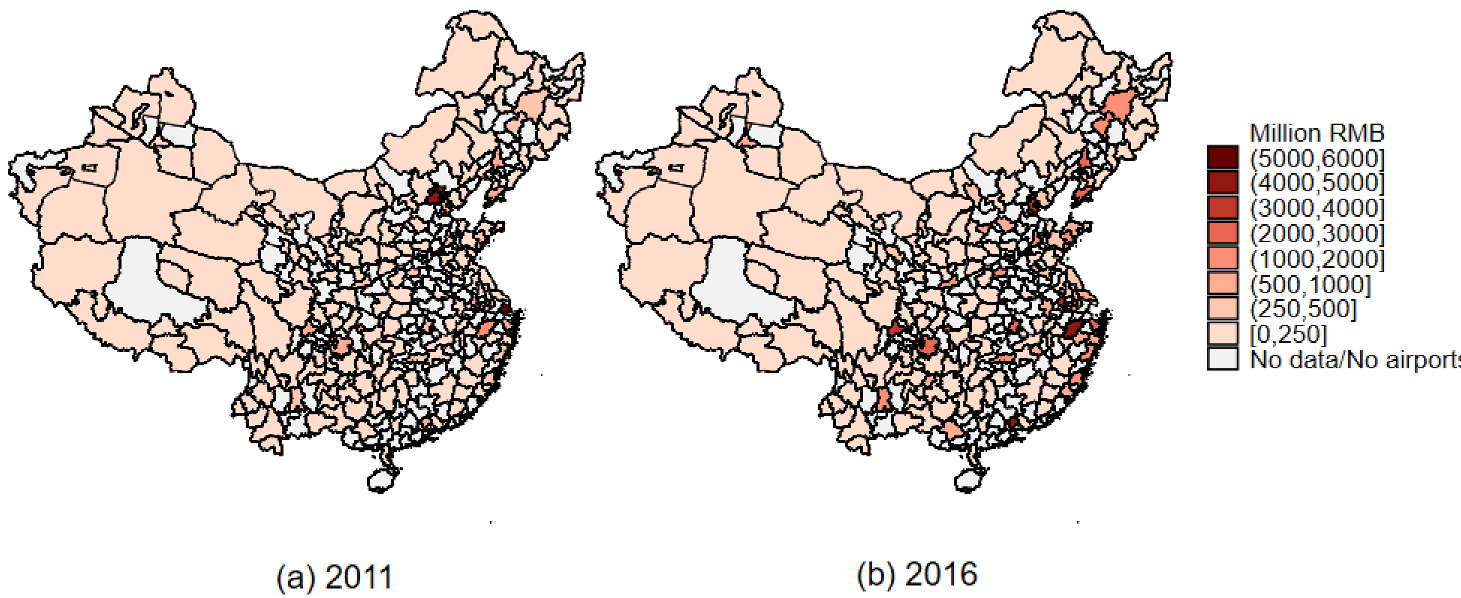



Figure 1: Chinese Cities With Overseas Transaction Values in 2011 and 2016

Notes: The unit of values are in millions RMB. We plot the value of card transactions on the maps of mainland China with cities. All overseas transactions are made by Chinese residents. We use the values in 2011 and 2016 on Panels (a) and (b), respectively. We use only the cities in our final dataset.

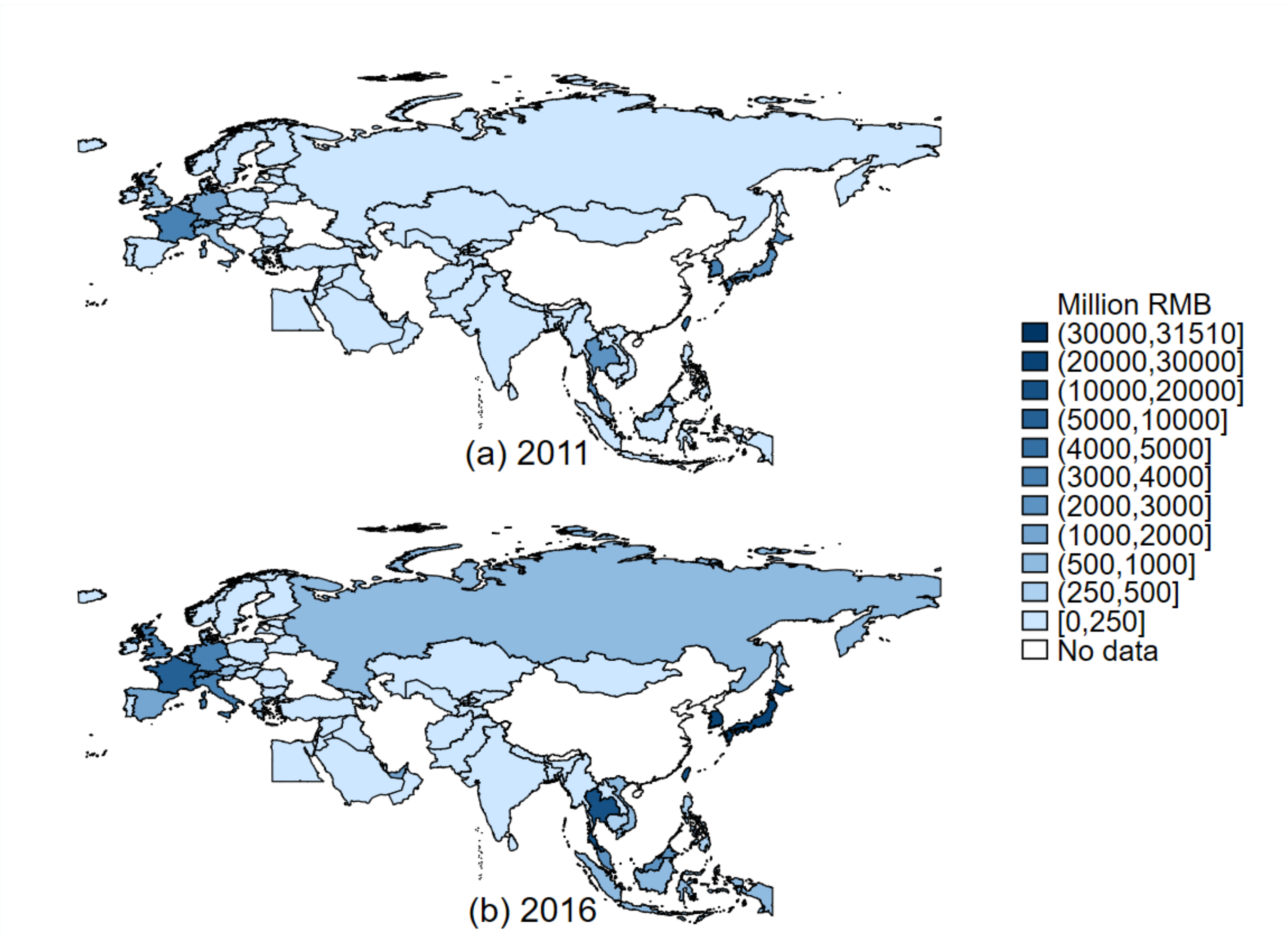



Figure 2: Travel Destinations With Card Transaction Values in 2011 and 2016

Note: The unit of values are in millions RMB. We plot the value of card transactions on the maps of foreign destinations. All transactions are made by Chinese residents. We use the values in 2011 and 2016 on Panels (a) and (b), respectively. We use only the countries in our final dataset.

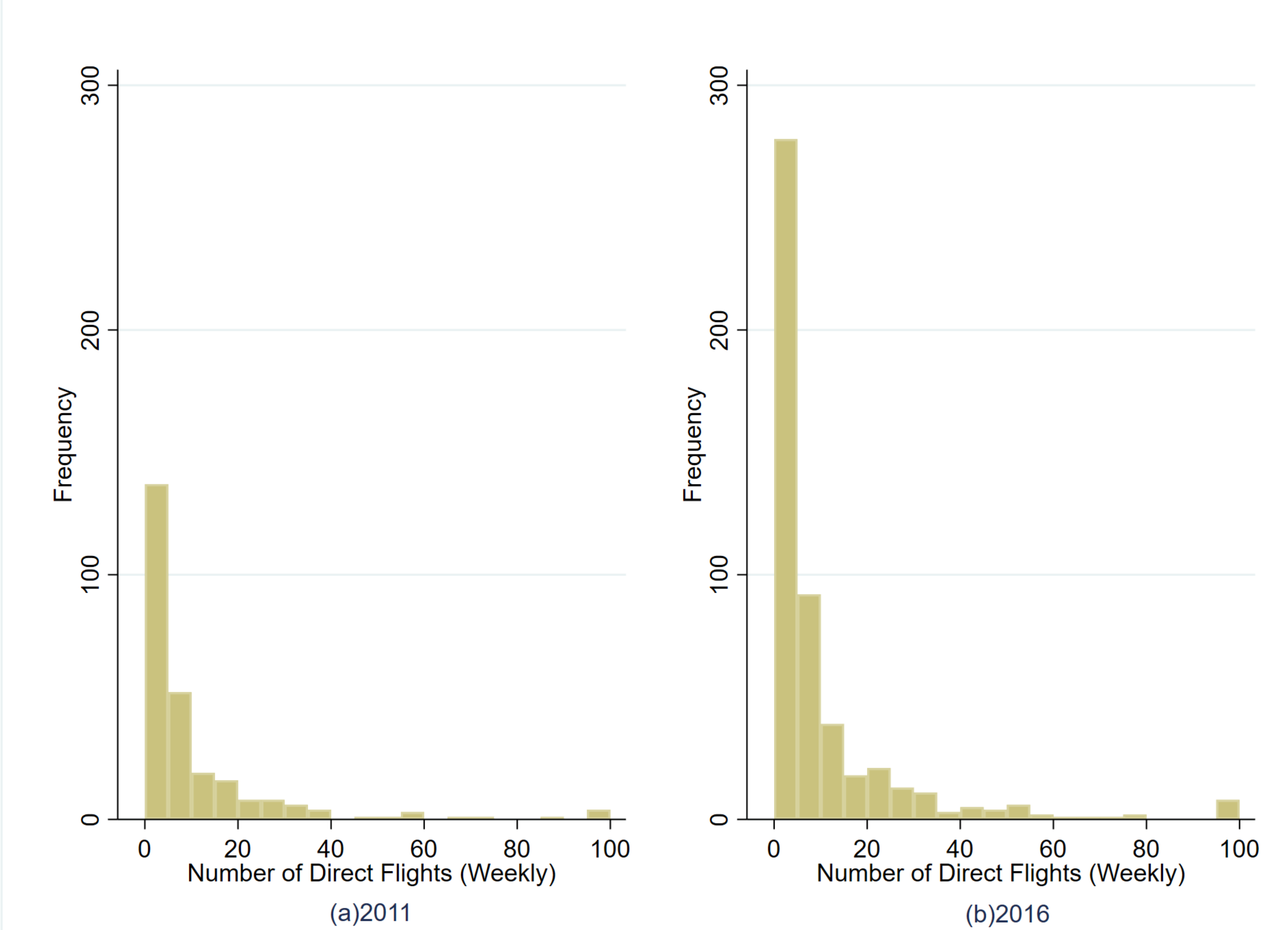
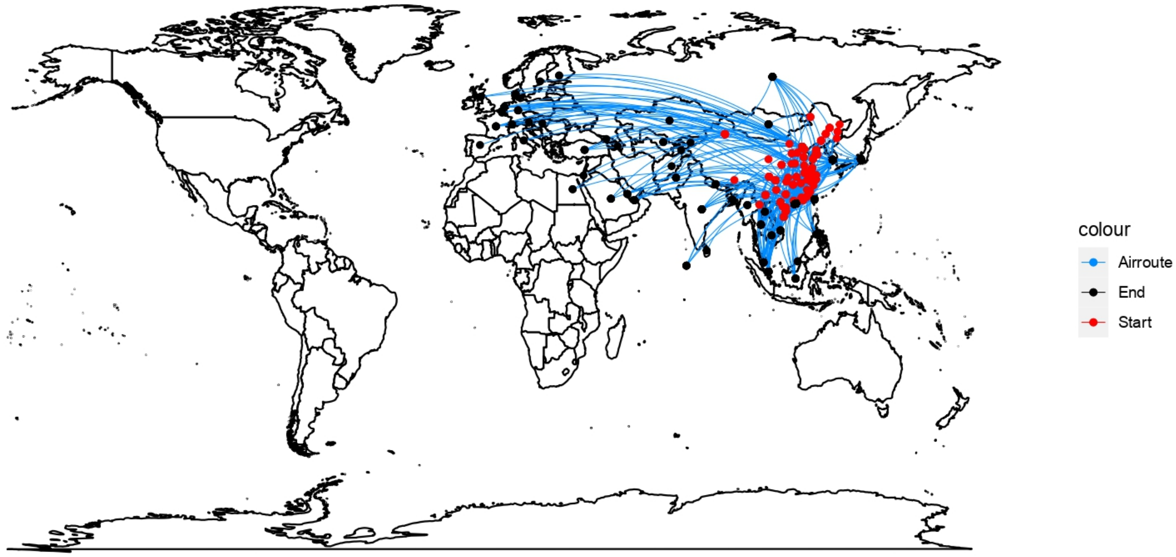
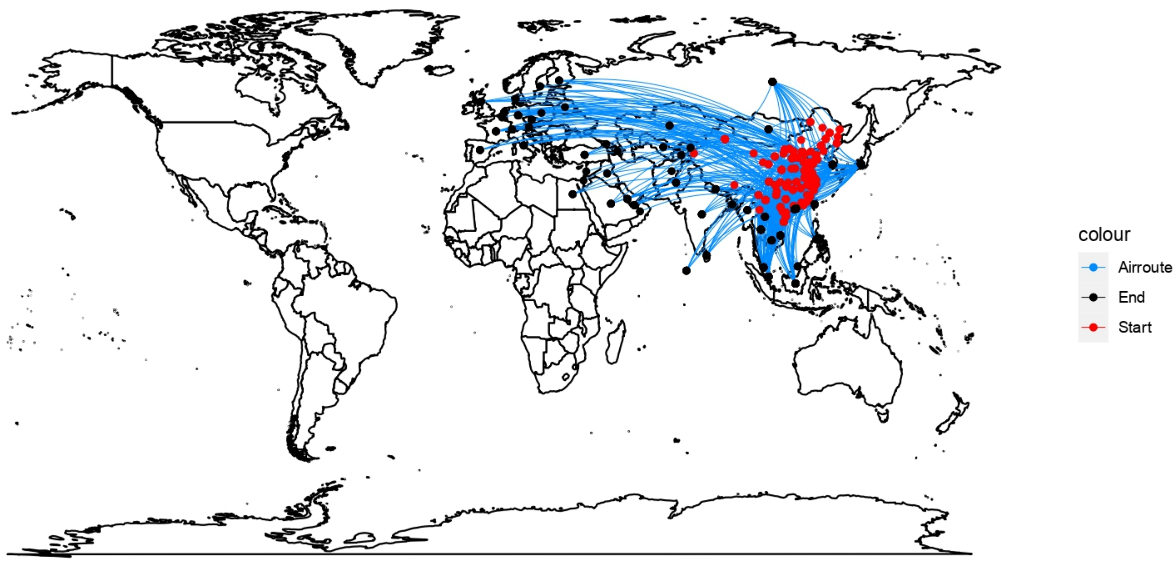



Figure 3: Distribution of the Number of Direct Flights By Chinese Cities

Notes: The figures show the distributions of the number of international direct flights (weekly) in each city in 2011 (Panel (a)) and in 2016 (Panel (b)). Only the cities with international direct flights are shown in the figures. The size of the bin is 10 weekly direct flights. Each bar represents the number of Chinese cities.



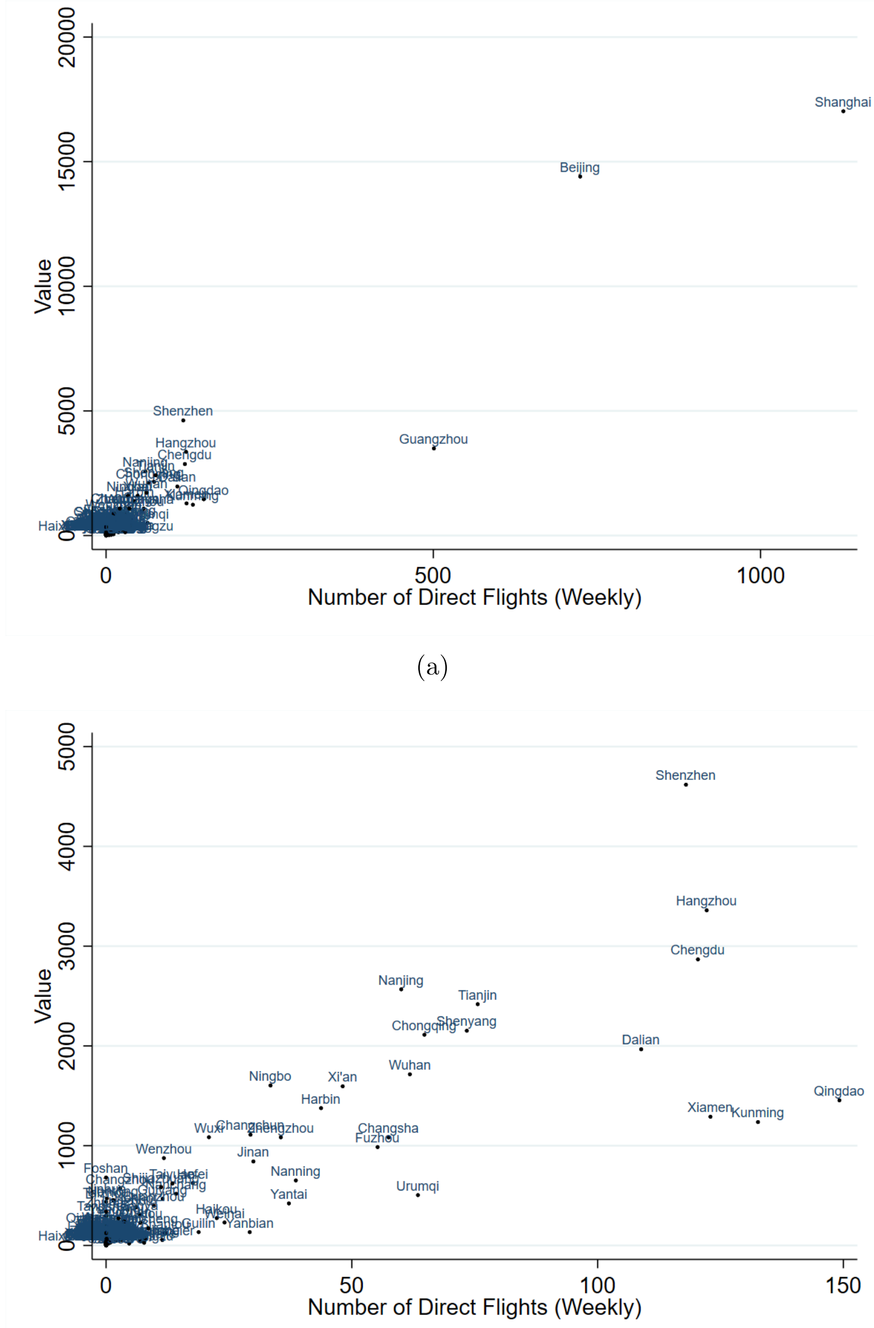

(a) 2011




(b) 2016

Figure 4: Direct Flight Routes in 2011 and 2016

Notes: The blue lines show the direct flight routes from Chinese cities (with red dots) to the destination countries (with black dots). Panels (a) and (b) show the international routes in 2011 and 2016, respectively. We use the air routes in our data sample.




(a)

(b)

Figure 5: Air Connectivity and the City-Level Card Transactions

Notes: In Panel (a), the y-axis represents the value of card transactions, and the x-axis displays the number of weekly international direct flights across Chinese cities. The transaction values and the number of flights are calculated as averages across the year and destination countries. For Panel (b), we excluded Shanghai, Beijing, and Guangzhou to focus on the other Chinese cities.

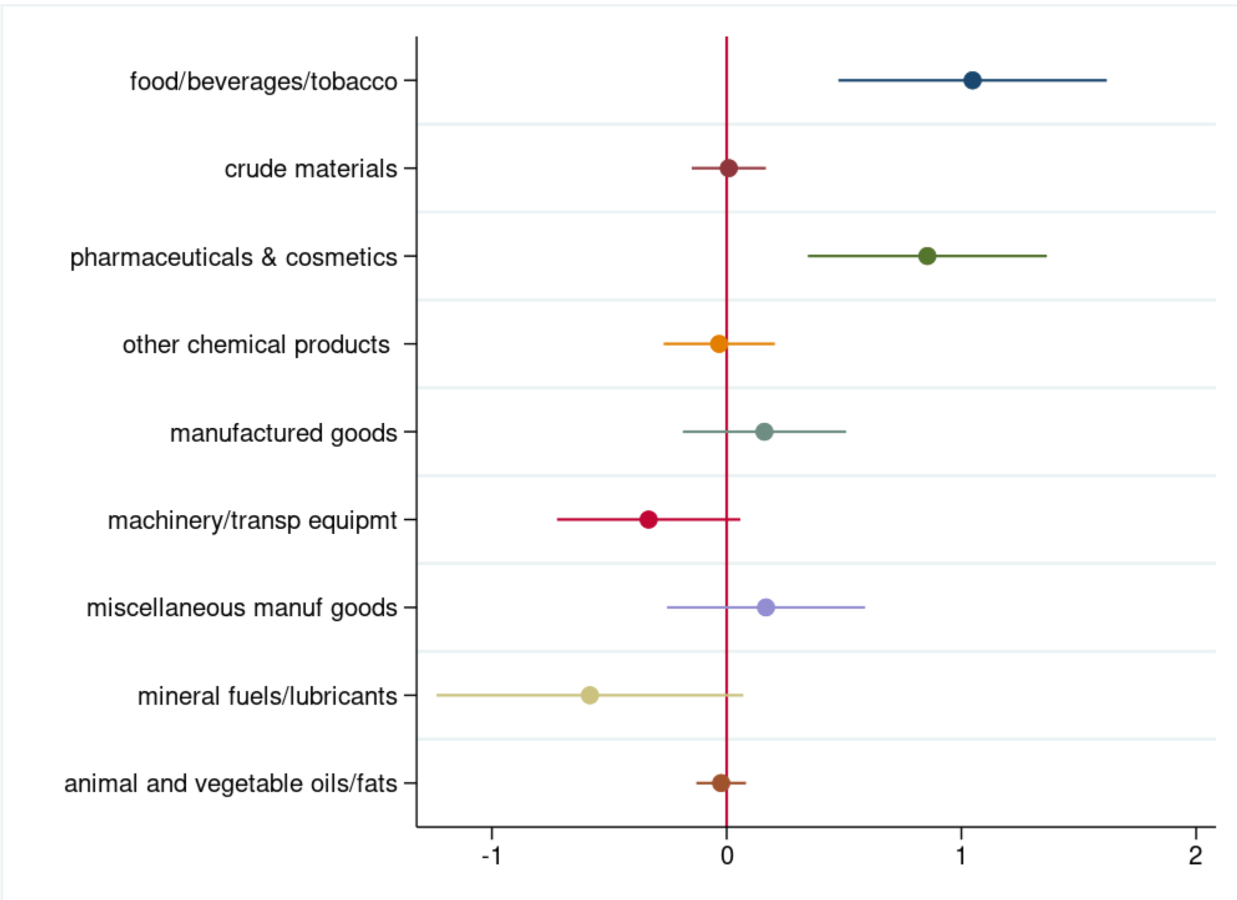



Figure 6: Estimates on Consumer Goods Imports by Industries

Notes: This figure shows the estimates of air connectivity on consumer goods imports from 2011 to 2016 by industries at the Chinese city-destination country level. Live animals are excluded from the food/beverages/tobacco industry.

# Tables

Table 1: Summary Statistics

| Variables | Mean | P(50) | Min | Max | SD | Observations |
|---|---|---|---|---|---|---|
| Main Data | | | | | | |
| *Card transactions* | | | | | | |
| Value (millions RMB) | 9.32 | 0.035 | 0 | 9,626.68 | 99.56 | 58,932 |
| Number of transactions | 5,246.67 | 16.00 | 0 | 5,399,033 | 78,527.36 | 58,932 |
| *Direct flights* | | | | | | |
| Weekly frequency | 0.45 | 0 | 0 | 473.56 | 5.72 | 58,932 |
| Supporting Data | | | | | | |
| *Imports* | | | | | | |
| Value (millions RMB) | 92.27 | 0.001 | 0 | 42071.6 | 10.60 | 58,932 |
| *Second Sino-Japanese war* | | | | | | |
| Number of casualties | 29,047.81 | 969.467 | 0 | 436,683.10 | 56,595.07 | 192 |

Notes: For variables we use in regressions, we report the mean, the median, the minimum and the maximum values, the standard deviations, and the number of observations.

Table 2: Baseline Results

| | Value of transactions | | | |
|---|---|---|---|---|
| | OLS | 2SLS | 2SLS | 2SLS |
| | (1) | (2) | (3) | (4) |
| Weekly Frequency | 0.075*** | 1.822*** | 1.874*** | 3.760*** |
| | (0.022) | (0.436) | (0.436) | (1.007) |
| 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 | 58,932 | 58,932 | 58,080 | 100,380 |
| First Stage | | | | |
| IV | | −39.419*** | −40.253*** | −22.393*** |
| | | (7.952) | (7.998) | (5.621) |
| KP Wald rk $F$-statistic | | 24.573 | 25.332 | 15.870 |
| KP LM statistic | | 24.831 | 25.623 | 16.061 |
| KP LM $p$-value | | 0.000 | 0.000 | 0.000 |
| AR Wald test $p$-value | | 0.000 | 0.000 | 0.000 |

Notes: Columns 1 and 2 show the main results. In column 3, we drop the city-country pairs that include Shanghai or Beijing. In column 4, we include cities without airports. 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.

Table 3: Robustness Checks

| | Number | Value of transactions | | |
|---|---|---|---|---|
| | | European regions | City groups | Quasi-experiment |
| | (1) | (2) | (3) | (4) |
| Weekly Frequency | 0.301*** | 1.730*** | 1.575*** | 0.954** |
| | (0.077) | (0.396) | (0.315) | (0.449) |
| Origin city-year FEs | Yes | Yes | Yes | No |
| Foreign country-year FEs | Yes | Yes | Yes | No |
| Origin city-foreign country FEs | Yes | Yes | Yes | No |
| Origin city FEs | No | No | No | Yes |
| Year FEs | No | No | No | Yes |
| Observations | 58,932 | 58,932 | 100,380 | 1,152 |
| First Stage | | | | |
| IV | −39.419*** | −41.516*** | −53.451*** | |
| | (7.952) | (7.921) | (10.227) | |
| Casualties × Boycott | | | | −0.012*** |
| | | | | (0.003) |
| KP Wald rk $F$-statistic | 24.573 | 27.470 | 27.314 | 11.633 |
| KP LM statistic | 24.831 | 27.600 | 27.762 | 10.742 |
| KP LM $p$-value | 0.000 | 0.000 | 0.004 | 0.001 |
| AR Wald test $p$-value | 0.000 | 0.000 | 0.000 | 0.012 |

Notes: The regression in column 1 uses the number of transactions as a dependent variable instead of the value of transactions. In column 2, we group European countries into four regions (Central and Eastern Europe, Northern Europe, Southern Europe, and Western Europe) and measure the frequency of direct flights for each European region. In column 3, we consider airports located within 200 km of each Chinese city. Column 4 shows the results for the quasi-experiment explained in Section 5.2.2. We add one to the alternative IV, Casualties × Boycott, and take a log of the value. 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.

Table 4: Effect of Air Connectivity on Goods Imports

| | Value of import | | |
|---|---|---|---|
| | Full Sample | Consumer goods | Non-consumer goods |
| | (1) | (2) | (3) |
| Weekly Frequency | $-0.267$ | 0.141 | $-0.278$ |
| | (0.502) | (0.366) | (0.496) |
| Origin city-year FEs | Yes | Yes | Yes |
| Foreign country-year FEs | Yes | Yes | Yes |
| Origin city-foreign country FEs | Yes | Yes | Yes |
| Observations | 58,932 | 58,932 | 58,932 |

Notes: This table presents the results of IV regressions with the value of imports. We do not report the first stage regression result as they are the same as that in Table 2. The categorization for consumer goods is from the UNCTAD and was obtained from the World Integrated Trade Solution (WITS) website. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Boycott and Cultural Shock

| | Values | | | |
|---|---|---|---|---|
| | Card transactions | Consumer goods | Food | Pharma+Cosmetics |
| | (1) | (2) | (3) | (4) |
| Weekly Frequency | 1.979*** | 0.130 | 1.079*** | 0.810*** |
| | (0.485) | (0.360) | (0.316) | (0.267) |
| Weekly Frequency × Boycott | $-0.208$*** | 0.000 | $-0.042$ | 0.059 |
| | (0.052) | (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 | 58,932 | 58,932 | 58,932 | 58,932 |

Notes: This table presents the results of IV regressions examining the impact of political conflicts on the effects of air connectivity on bilateral trade. 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 column 4 analyzes the pharmaceutical and cosmetics industries. The political conflicts affecting Chinese consumers include the boycott of South Korea in 2016, the boycott of Japan in 2012, the boycott of the Philippines in 2012, and the boycott of Norway in 2011. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# Appendix A Appendix Tables

## A.1 Destination Countries

There are 72 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: List of Cross-Border Travel Destination

| | | | |
|---|---|---|---|
| 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 | Syrian Arab Rep | 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 and the Share of the Transactions

The two biggest Chinese cities, Beijing and Shanghai, have the largest numbers of direct flights and the highest value (or number) of card transactions. One of our concerns is that the values (or numbers) 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 and numbers. 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 4.7% on average. This implies that the transaction values are not concentrated in a handful of city-country pairs. We observe the same for the number of transactions in Panel (b) of Table A.2.

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

| City | Country | Average (yearly) | Share |
|---|---|---|---|
| Value of transactions (in million RMB): | | | |
| Shanghai | Japan | 4,330.70 | 0.047 |
| Shanghai | South Korea | 2,807.33 | 0.031 |
| Beijing | Japan | 2,679.53 | 0.029 |
| Beijing | South Korea | 2,622.70 | 0.029 |
| Shanghai | Taiwan | 2,054.25 | 0.022 |
| Number of transactions (in million): | | | |
| Shanghai | Japan | 2.41 | 0.047 |
| Shanghai | South Korea | 2.20 | 0.043 |
| Beijing | South Korea | 1.91 | 0.037 |
| Beijing | Japan | 1.47 | 0.029 |
| Chengdu | Netherlands | 1.29 | 0.025 |

Note: This table shows the Chinese city-foreign country pairs with the five largest average transaction values and the five largest average numbers of transactions. Averages of the values and the numbers of card transactions are means over the sample period. The shares are the average values (or numbers) of transactions over the total average values (or numbers). The total average value is 91,532.64 million RMB. The total average number of transactions is 51.51 million.

## A.3 Airport Connectivity in 2011 and 2016

One of the components of our IV is the share of the number of flights reaching a foreign country to total direct flights across the world. In Table A.4, we list the counties with the number of total inbound flights in 2011 and 2016. The countries with larger changes in that number contribute to variations in our IV.

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

| Country | 2011 | 2016 | Change | Percentage Change |
|---|---|---|---|---|
| United Arab Emirates | 203,777 | 312,501 | 108,724 | 53.4% |
| United Kingdom | 651,621 | 756,802 | 105,181 | 16.1% |
| Turkey | 152,434 | 242,067 | 89,633 | 58.8% |
| Spain | 420,922 | 498,543 | 77,621 | 18.4% |
| Saudi Arabia | 80,396 | 148,102 | 67,706 | 84.2% |
| Japan | 120,980 | 183,660 | 62,680 | 51.8% |
| South Korea | 86,870 | 135,380 | 48,510 | 54.7% |
| Qatar | 65,157 | 110,719 | 45,562 | 69.93% |
| Thailand | 105,231 | 149,361 | 44,130 | 41.9% |
| Taiwan | 66,733 | 105,584 | 38,851 | 58.2% |
| Italy | 353,278 | 391,240 | 37,962 | 10.7% |
| India | 124969 | 162,113 | 37,144 | 29.7% |
| Netherlands | 210,629 | 247,204 | 36,575 | 17.4% |
| Greece | 76,903 | 108,435 | 31,532 | 41.0% |
| Malaysia | 101,771 | 132,548 | 30,777 | 30.2% |
| Poland | 88,056 | 118,214 | 30,158 | 34.2% |
| Germany | 649,606 | 679,307 | 29,701 | 4.6% |
| Portugal | 99,368 | 12,7044 | 27,676 | 27.9% |
| Ireland | 93,007 | 119,503 | 26,496 | 28.5% |
| France | 457,647 | 483,472 | 25,825 | 5.6% |

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

Table A.4: The Share of Inbound Flights from China in 2011 and 2016

| Country | Share 2011 | Share 2016 |
|---|---|---|
| United Arab Emirates | 0.0159 | 0.0143 |
| United Kingdom | 0.0024 | 0.0040 |
| Turkey | 0.0060 | 0.0047 |
| Spain | 0.0006 | 0.0010 |
| Saudi Arabia | 0.0016 | 0.0021 |
| Japan | 0.2131 | 0.2285 |
| South Korea | 0.2873 | 0.3153 |
| Qatar | 0.0141 | 0.0144 |
| Thailand | 0.0861 | 0.2618 |
| Taiwan | 0.2368 | 0.2465 |
| Italy | 0.0028 | 0.0047 |
| India | 0.0134 | 0.0129 |
| Netherlands | 0.0088 | 0.0094 |
| Greece | 0 | 0 |
| Malaysia | 0.0675 | 0.0887 |
| Poland | 0 | 0.0017 |
| Germany | 0.0059 | 0.0067 |
| Portugal | 0 | 0 |
| Ireland | 0 | 0 |
| France | 0.0056 | 0.0083 |

Note: This table lists the share of inbound flights from China of 20 countries with the largest change in the number of inbound flights from 2011 to 2016.