Connecting to the World: Heterogeneous Effects of Air Connectivity on Trade*

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Abstract

We study how air connectivity shapes 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 2.3% increase in cross-border card transaction value. The development of air connectivity promotes cross-border travel, but this effect is diminished by negative shocks to consumer tastes and preferences. These negative shocks affect only trade in travel services, with no effect on trade in goods.

Keywords: Cross-Border Travel, Bilateral Trade, Air Transportation and Trade Costs
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). If travel costs decrease due to improvements in air connectivity, more consumers might start traveling abroad, which can enhance domestic welfare. The local government plays a role in reducing the cost of international travel by setting up and increasing air connectivity abroad. This policy measure involves a large investment in airport expansion; evaluating the potential costs and benefits is complicated by general equilibrium consumer responses. For example, a new air connection may divert travelers from existing air connections, which limits the potential benefits of increasing air connectivity abroad. On the other hand, increasing air connectivity may generate a positive externality by increasing the flow of goods between newly air-connected markets. Despite the policy importance, there is little empirical evidence to quantify how much air connectivity promotes cross-border trade in services.

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.

Exploiting our panel data structure, our identification strategy is based on variation in air connectivity over time within a 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

[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).

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, Dorn, and Hanson (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 2.3% 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.

We further analyze the effect of improvement in air connectivity on the value of Chinese imports using Chinese customs data. The results vary across industries. In particular, a higher frequency of weekly direct flights increases the value of imports of products that are mostly transported by air (e.g., food/beverages and pharmaceuticals/cosmetics). Moreover, we look at how consumer tastes and preferences toward foreign countries affect our findings by exploiting political conflicts as exogenous shocks. We find that the negative sentiments toward foreign countries diminish the positive effect of air connectivity on cross-border travel, while these negative shocks to consumer preferences do not affect trade in goods.

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 growth (Hovhannisyan and Keller 2015; Campante and Yanagizawa-Drott 2017), international trade (Cristea 2011; Alderighi and Gaggero 2017; Wang, Wang, and Zhou 2021; Söderlund 2022), foreign investment (Campante and Yanagizawa-Drott 2017; Fageda 2017; Tanaka 2019), and cross-border mergers and acquisitions (Zhang, Kandilov, and Walker 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, Friberg, and Wilander (2007) and Friberg, Steen, and Ulsaker (2022) use data of Sweden and Denmark, while Chandra, Head, and Tappata (2014) and Baggs, Fung, and Lapham (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 trade data. Section 7 concludes.

[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.

[4]These papers show that travel costs (proxied by distance) and price differential drive cross-border travel. For example, Chandra, Head, and Tappata (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, Fung, and Lapham (2018) show similar results for consumers as Chandra, Head, and Tappata (2014) but also show results on how the cross-border travel of Canadians to the US hurts Canadian retailers.

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 analyze the effect of air connectivity on Chinese overseas travel spending. We also use other data for further analysis, such as 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 cross-border card transaction value.

2.1 Data Sources

(i) Chinese overseas card transactions

The unique dataset of Chinese overseas card transactions enables us to analyze Chinese overseas travel spending. We collect a dataset on card transactions between 2011 and 2016 from a consumer card provider in China. The data comes from the transactions that Chinese cardholders make outside China (i.e., the data exclude online transactions).[5] For each transaction, we observe the cardholder's city of residence, the country where the transaction was made, and the time and value of the transaction. We impute cities of residence using past card transactions, assuming that the cardholder lives in the city with the most card transactions among all cities in which they used their card. The travel destinations in the data are the countries of the Belt and Road Initiative in Eurasia, Japan, and EU countries.[6] For confidentiality purposes, the card network aggregates the data at the year-city of residence-destination country level.

(ii) Worldwide flight schedules

The air connectivity data comes from OAG Analyser. This database provides worldwide

[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))

[6]A list of countries of the Belt and Road Initiative is 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.

flight schedules, including 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 focus on direct flights to measure air connectivity, and therefore we extract the yearly number of direct flights between a given Chinese city and a destination country. We define frequency (or capacity, in terms of the number of seats) as the average number of weekly non-stop direct flights (or average non-stop capacity) between an origin city and a destination country. The weekly frequency and capacity of direct flights are our main measures of air connectivity. We also add the names of cities and countries to the flight schedule using the correspondence tables provided by OAG.[7]

(iii) Chinese customs data

The trade data come from the Chinese transactions-level database collected by China's General Administration of Customs (CGAC) for the period of 2011-2016. This dataset contains rich information for all Chinese export and import transactions over this period. We use the information on Chinese imports from this dataset. For each import transaction, we observe the company name, company code, the city where a company locates, product name, product code (at the HS 8-digit level), country (source of imports), time (year and month), and value of the transaction. Our data also classify transactions into ordinary trade and processing trade.[8]

(iv) Number of casualties during the second Sino-Japanese war

The data for the number of casualties during the second Sino-Japanese war comes from Chi (1987). This source provides information on the number of people who suffered minor or major wounds or died during the second Sino-Japanese war at the provincial level. In order to obtain the number of casualties at the city level, we use the city population in

[7]The correspondence tables are provided through Power Table Report in Schedule Analyser. OAG shows the name of the cities where airports mainly provide air transportation services. The airports in the following four cities are located in different cities nearby, but they are shown in the OAG data: Taizhou(Jiangsu), Haidong (Qinghai), Xianyang (Shaanxi), and Shannan (Tibet).

[8]We do not have information on the firm location (city) for the year 2016. We find the city code using the first four-digit of the company code and a concordance table (link). We subtract the first four-digit of the area code as the city code because our data is at the prefecture city level.

the year 1934 collected by China City and County Land and Population Census.[9] From this dataset, we can observe the province name, city name, and population. We estimate the city-level number of casualties using the share of the city population in the total province-level population.[10]

2.2 Descriptive Statistics

We merge the two main datasets, the Chinese card transaction data and the flight data. In the final dataset, we observe 192 unique Chinese cities (origins) and 72 unique foreign countries (destinations), with a total of 58,932 origin-destination pairs.[11] The destination countries are listed in Table A.1.

Table 1 reports 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. The import of a sample city from a foreign country is 92.27 million RMB per year.

On average, each origin city-destination country pair has 0.71 weekly flights, with just over 147 available total seats. Similar to the transaction value and numbers, the distributions of both frequency and capacity are right-skewed, likely because some cities have larger airports that attract more direct flights.

2.3 Stylized Facts

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

[9] This dataset is published by the Department of the Interior, Statistical Division in the year 1935.

[10] 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 second Sino-Japanese war.

[11] 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, the countries without airports (The State of Palestine, Liechtenstein, and Vatican City State) cannot be matched with flight data.

Fact (i): Regional differences in transaction value

Figure 1 shows the value of transactions on a map of mainland China with cities. We observe that some cities have experienced a large increase in transaction value, while some cities 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 China. For example, the total overseas transactions have increased by around 421% in Wuhan (one of the inland cities, in Hubei Province), 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 value of the total flow from China to Japan was around 2,608 million RMB in 2011 and 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 (ii): Chinese cities became more connected by 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 larger 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 network. Figure 4 shows that there were more direct flight routes connecting Chinese cities with foreign countries in 2016 (Panel (b)) than in 2011 (Panel (a)). Moreover, some of the cities got new direct flights to overseas destinations, such as Lijiang and Yichang. In fact, 24 cities did not have direct flights to any foreign countries in 2011 but got direct flights by 2016.

Fact (iii): There is a positive relationship between air connectivity and card transactions

Panel (a) of Figure 5 shows there is a positive correlation between the average value of card transactions across cities (depicted on the y-axis) and the average number of direct flights (depicted on the x-axis). In Panel (b), we instead use the average number of transactions on the y-axis and the number of direct flights as a measure of air connectivity, finding a similar positive correlation. We empirically investigate these positive relationships in the following sections.[12]

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, Mayer, and Ries (2008) who introduce a model for bilateral service trade to derive a gravity-type equation for trade in the travel service sector.

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 ωs 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 $X_i = \beta_i Y_i$

[12] 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).

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 τ_{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 θ 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 ϵ_{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[13]:

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

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, τ_{ij}, and the price in the destination, p_j.

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

[13] 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

cultural relationships. We can express the total trade costs, τ_{ijt}, as

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

where D_{ijt} is air flight connectivity at t, and α_{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, ϵ_{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. Our baseline regression specification is

$$\ln X_{ijt} = \alpha + \beta_1 \ln D_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}, \tag{5}$$

where $\ln X_{ijt}$ denotes the log of total card transactions by consumers from city i in country j, and $\ln D_{ijt}$ is the level of air connectivity (i.e., number of weekly direct flights between i and j).[14] We include city-country fixed effects, δ_{ij}, to capture time-invariant unobserved hetero-

[14] We add one to both value and air connectivity before taking logs to deal with zero values.

geneity that induces consumers in i to visit j, including cultural and business relationships. Origin-city time-varying fixed effects, η_{it}, account for origin-specific time-variant factors, such as city income. Additionally, destination-country time-varying fixed effects, κ_{jt}, control for the 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, β_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, β_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 λ_{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.[15] This IV is analogous to the one developed by Autor, Dorn, and Hanson (2013), who instrument for

[15] We exclude the flights from China to construct the value, λ_{jt}.

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 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.[16] We assume that distance affects our dependent variable (value of card transactions) only through air connectivity (our endogenous variable).[17] Multiplying the distance between city i and country j, $dist_{ij}$, by the country-time level share λ_{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, λ_{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).[18] The country opened the world's largest airline terminal in Dubai in 2008. Since then, its share of global

[16] 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).

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

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

international direct flights (i.e., the first term in our instrumental variable) has increased substantially. Appendix A.3 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% 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:

$$\ln D_{ijt} = \gamma + \beta_0 Z_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \xi_{ijt} \qquad \text{(first stage)} \tag{7}$$

$$\ln X_{ijt} = \alpha + \beta_1 \ln D_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}. \qquad \text{(second stage)}, \tag{8}$$

where we define Z_{ijt} in equation (6). Our first stage coefficient, β_0, 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, 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, ξ. Our second stage coefficient of interest, β_1, delivers the causal impact of air connectivity on card transactions made by consumers from city i in destination country j.

5 Results

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. Further, we discuss the impact of air connectivity on trade in goods and compare such impact to that on service trade. Finally, we present some results relating to destination heterogeneity.

5.1 Main Results: Trade in Travel Services

Table 2 shows the effect of air connectivity on cross-border travel 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 OLS coefficient on air connectivity is positive and significant (column 1). Specifically, a 1% increase in the weekly frequency of direct flights leads to a 0.12% increase in cross-border travel spending.

The result from our 2SLS/IV estimation is in column 2. 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 11.19, which suggests that we can reject the null of a weak instrument.[19] The second-stage results find that a 1% increase in the weekly frequency of direct flights leads to a 2.3% increase in cross-border card transaction value.

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 λ_{jt} in equation 6).

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

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 are robust using alternative measures of travel spending (i.e., dependent variable). We also consider the sensitivity of our results to different sample constructions. Finally, we consider an alternative identification approach for causal inference.

5.2.1 Alternative Variables

One of the robustness checks is to employ alternative specifications of our dependent variable. First, we apply the inverse hyperbolic sine (IHS) transformation to the value of transactions because Table 1 shows that a non-trivial fraction of city-country pairs have zero card transactions.[20] The IHS function can approximate the natural logarithm of the variable and allows the retaining of zero-valued observations (Bellemare and Wichman 2020). The IHS result appears in column 3 of Table 2. Encouragingly, the coefficient is very similar to the one in column 2 in terms of size, significance, and sign.

Second, we replace the value of card transactions with the number of card transactions. Column 4 of Table 2 reports that a 1% increase in weekly direct flights leads to a 0.17% increase in the number of card transactions. The positive and statistically significant result is similar to the main result using the value of transactions (column 2 of Table 2).

5.2.2 Different Sample Sizes

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 driven by the travelers from these two cities.[21] We drop the city-country pairs that include Shanghai or Beijing and re-

[20] The result of a Poisson Pseudo-Maximum-Likelihood (PPLM) regression is also similar to the one in our OLS result (column 1). One can run PPML regressions with IVs and fixed effects using the control function method. However, the control function method requires endogenous variables to be continuous (Wooldridge, 2015). Our endogenous variable, the weekly frequency of direct flight, contains a lot of zero (more than 90%), and therefore we are not able to apply the control function method to run PPML regressions with our IV and fixed effects.

[21] 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).

estimate our OLS and 2SLS specifications to see whether our findings hold in this restricted sample. Columns 1 and 2 of Table 3 show that both OLS and 2SLS coefficients with the restricted sample are very similar to the ones with the full sample (shown in columns 1 and 3 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 columns 3 and 4 of Table 3. 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.

5.2.3 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.

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 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.[22] 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 1 of Table 4 shows the result of OLS regression using the card transaction value as a dependent variable and our new IV measure, Z_{it}, as the main explanatory variable. The coefficient on the IV is negative and significant. This shows that an exogenous shock in the political conflict between China and Japan leads to a larger relative decrease in cross-border travel for the city with a larger number of casualties compared to the one with a smaller number of casualties.

The result with the alternative IV specification is in column 2. 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 1.5% increase in card transaction value made by Chinese consumers in Japan.

[22] 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 the negative 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. For example, 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.[23] 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.[24] A increase in the weekly frequency of direct flights can affect trade in goods directly (by increasing freight capacity) and indirectly (by reducing the costs of business travel).

We estimate the effect of air connectivity on the import of goods from country j to Chinese city i. We run the IV regression introduced in Section 4.3 and use the value of import as a dependent variable instead of the card transaction value (i.e., X_{ijt} in equation 8).

The results are in Table 5.[25] Column 1 shows that the coefficient on air connectivity is negative and significant. Specifically, a 1% increase in the weekly frequency of direct flights leads to a 1.09% decrease in the value of imports. This result indicates that improvement in air connectivity between Chinese city i and country j decreases the import of goods between them. We separate the import data into the import via ordinary trade and the one through processing trade. Interestingly, the negative and significant coefficient appears only with the

[23] Similarly, Bernard et al. (2017) also show the lower cost of travel enhances the creation of buyer-seller relationships by exploiting the new opening of a high-speed train line in Japan.

[24] 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).

[25] We do not report the results of the first stage regression because they are the same as that in Table 2.

data of ordinary trade (columns 2 and 3). This suggests that the negative and significant result in column 1 is mainly driven by non-processing trade that ties closer to final goods consumers than processing trade.

To explore this negative and significant result, we separate the Chinese import data into the data in different industries (based on the one-digit level of the SITC codes) and run regressions using the data of each industry.[26] The results vary depending on industry (Figure 6). Interestingly, the imports of food/beverage and pharmaceutical/cosmetic products increase by 1 or 2% by a 1% increase in the weekly frequency of direct flights. These products are mostly transported by air. For example, food/beverage are perishable and time-sensitive products (Djankov et al. 2010). Pharmaceuticals have higher unit values compared to other products and are shipped primarily by a fast and expensive mode of shipment (Harrigan 2010).[27]

Contrarily, we find negative and significant coefficients on chemical products and mineral fuel/lubricants. Specifically, a 1% increase in the weekly frequency of direct flights leads to a 2% decline in the import values. These products are often bulky and transported by sea. Interestingly, we find a substitution between cross-border travel and international trade for these types of products.

6.2 Negative Shocks to Consumer Preferences

We showed that the improvement in air connectivity promotes cross-border travel, and the effect on imports of goods varies across industries. We study whether these findings would change by the characteristics of destination countries, which affect the preferences and choices of Chinese consumers. Specifically, we analyze the effects of the enhancement of air connectivity on trade in travel services and goods by exploiting variations in political conflicts between the destination country and China as an exogenous shock to consumer preferences. We expect that a more hostile sentiment towards a particular destination may attenuate the effects of air connectivity on cross-border travel and bilateral trade.

[26] The industry classification is the Standard International Trade Classification, Revision 4.

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

During the data period, there are four notable conflicts between China and Japan, the Philippines, South Korea, and Norway.[28] 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 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.[29] 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, *boycott*, 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. Second, we add the interaction term between the log of the weekly frequency of direct flights ($\ln D_{ijt}$ in equations 7 and 8) and *boycott* to the 2SLS specification introduced in Section 4.3. We run regressions using the data of card transactions and imports of goods between Chinese cities and four countries of interest (i.e., Japan, the Philippines, Korea, and Norway).[30]

We find the negative and significant coefficient on the interaction term between air connectivity and boycott (column 1 of Table 6). This result shows 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

[28] 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).

[29] 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.

[30] 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.

significant with the data of ordinary import (column 2). We continue to see statistically insignificant results using only the import data in the food/beverages and pharmaceuticals/cosmetics industries that experienced an increase in the value of imports by the development of air connectivity (the result is shown in Section 6.1). Overall, the results suggest that a rise in political conflicts—an adverse shock of consumer preference towards destination countries—can offset the promoting effect of air connectivity on cross-border travel and trade.

7 Conclusion

This paper studies the effect of air connectivity on trade in travel services. Our unique data allow us to observe the value of card transactions from Chinese cities to foreign countries. We instrument for air connectivity using the destination's comparative advantage in air transportation and the distance between a Chinese city-foreign country pair. Our 2SLS estimates indicate that a 1% increase in the weekly frequency of direct flights between a Chinese city-destination country pair leads to a 2.3% increase in the value of transactions by consumers from that city in the newly connected country. Our results are robust to alternative outcome definitions and sample sizes. We extend our analysis and look at the effect of air connectivity on trade in goods. The result shows that the improvement in air transportation networks raises the value of imports of products that are mostly transported by air, such as food/beverages and pharmaceuticals/cosmetics.

Improvements in air connectivity reduce travel costs and thus promote demand for travel services. Our study proves that relationship, but moreover, our unique Chinese city-foreign country level data enable us to test how consumer preferences toward a destination country affect our findings. We exploit political conflicts as exogenous shocks that affect consumer tastes. Interestingly, we find that the effect of air connectivity on cross-border travel is diminished by consumers' negative sentiments towards the destination countries that are in conflict with China. These negative shocks affect only trade in travel services, with no effect on trade in goods.

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

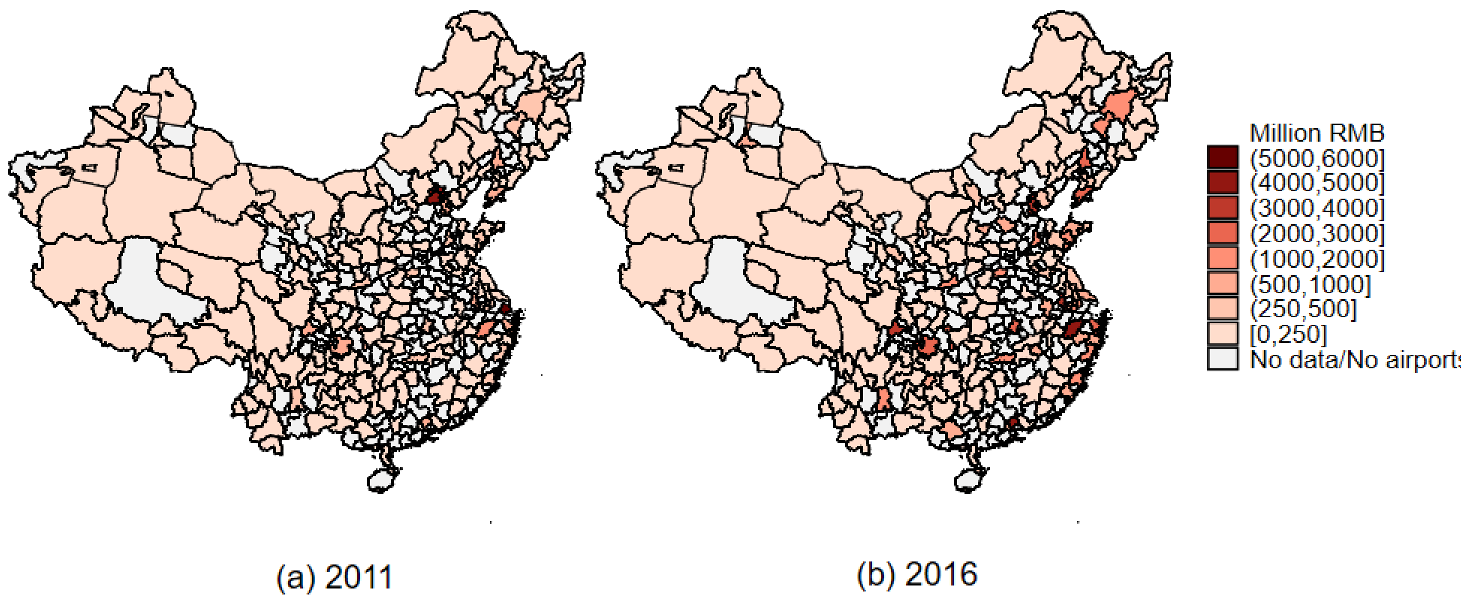


Figure 1: Chinese Cities With Overseas Transaction Values in 2011 and 2016

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.

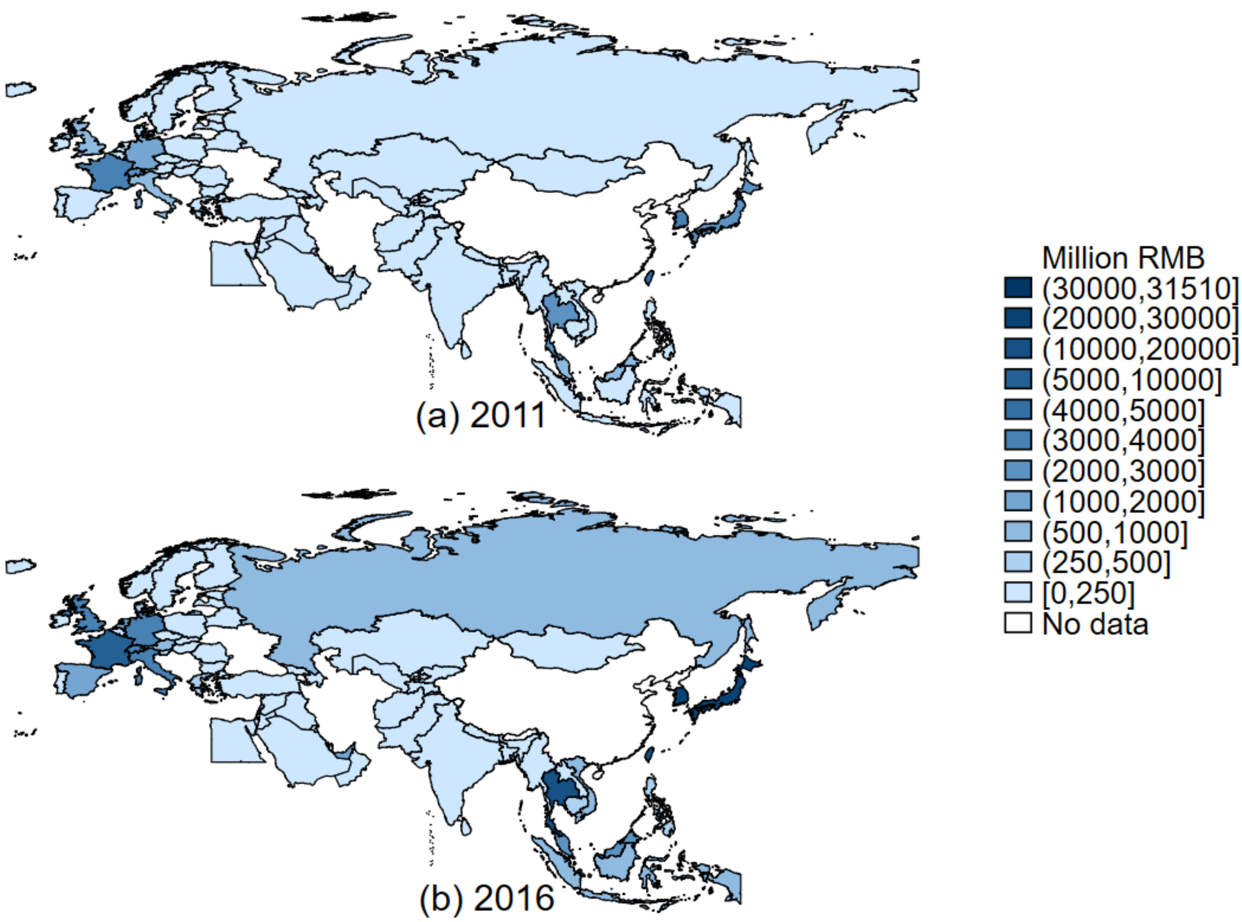
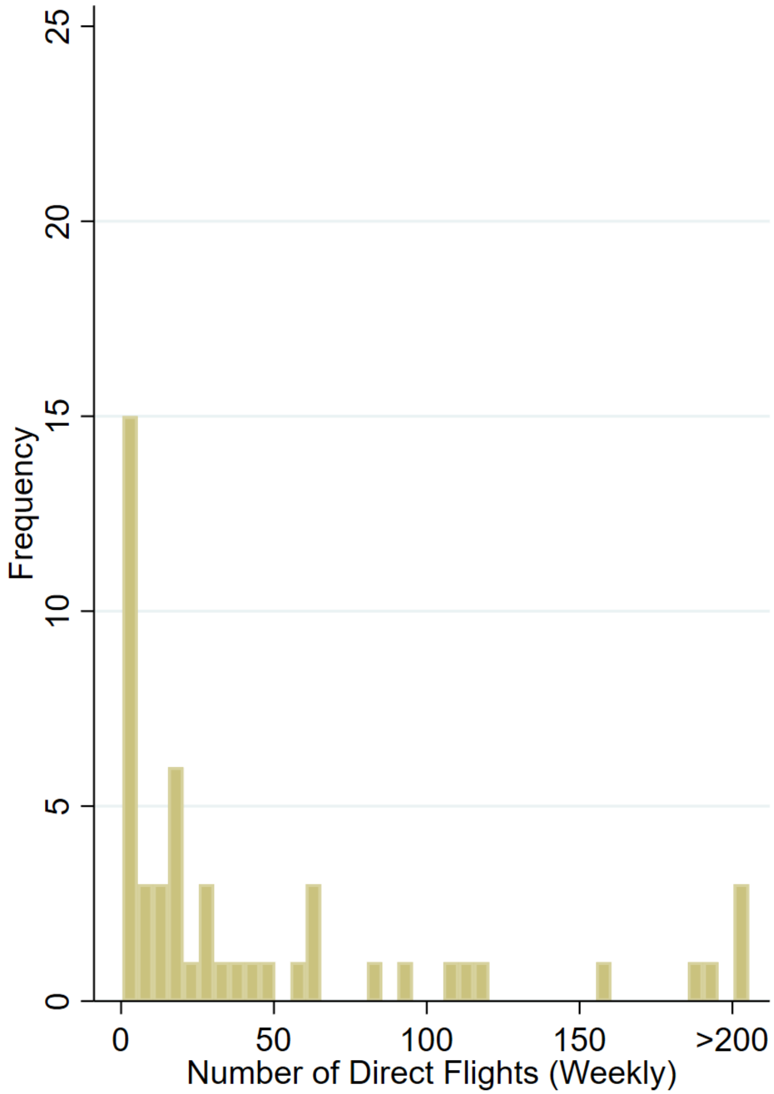
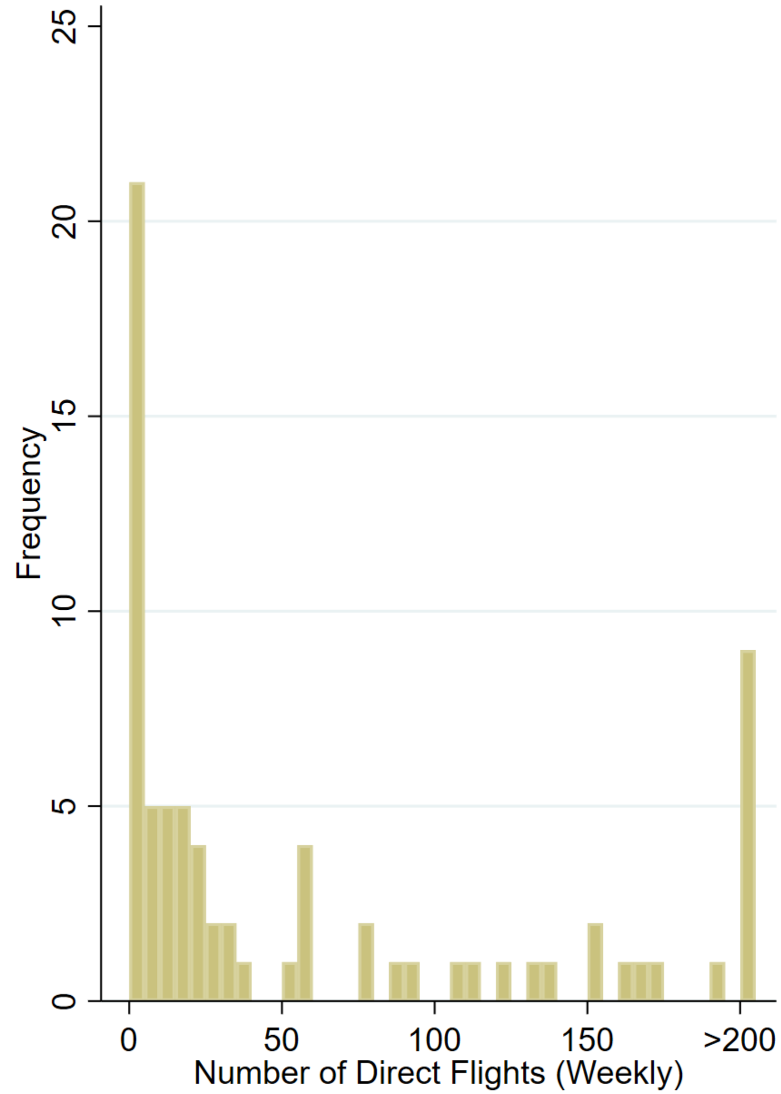


Figure 2: Travel Destinations With Card Transaction Values in 2011 and 2016

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.



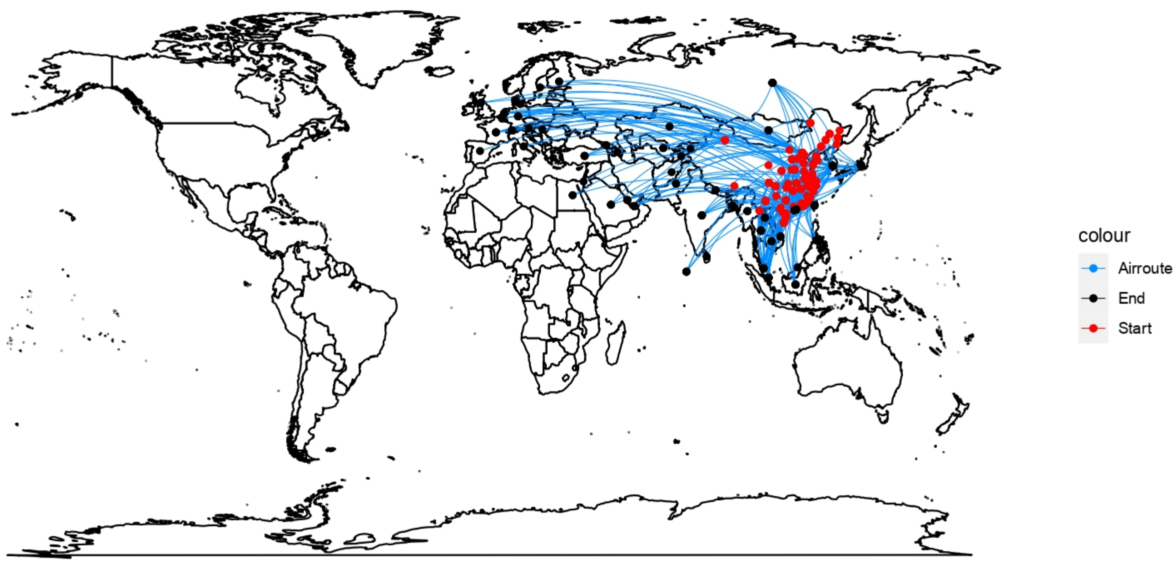
(a) 2011



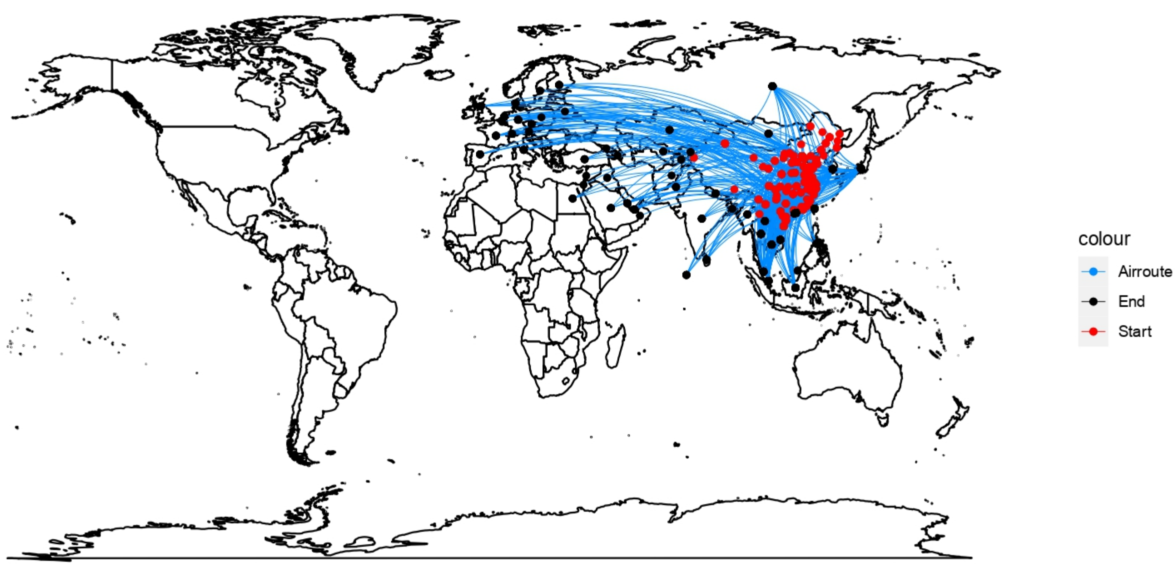
(b) 2016

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.



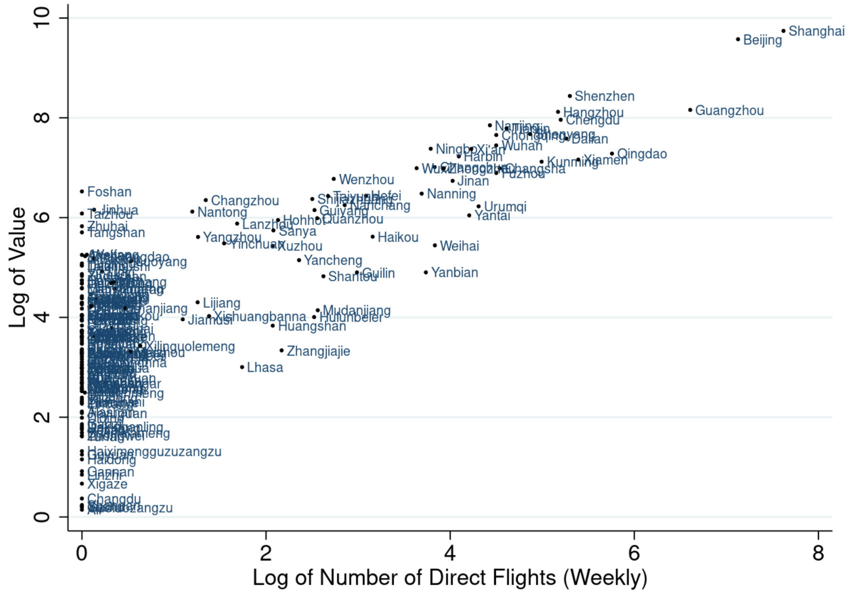
(a) 2011



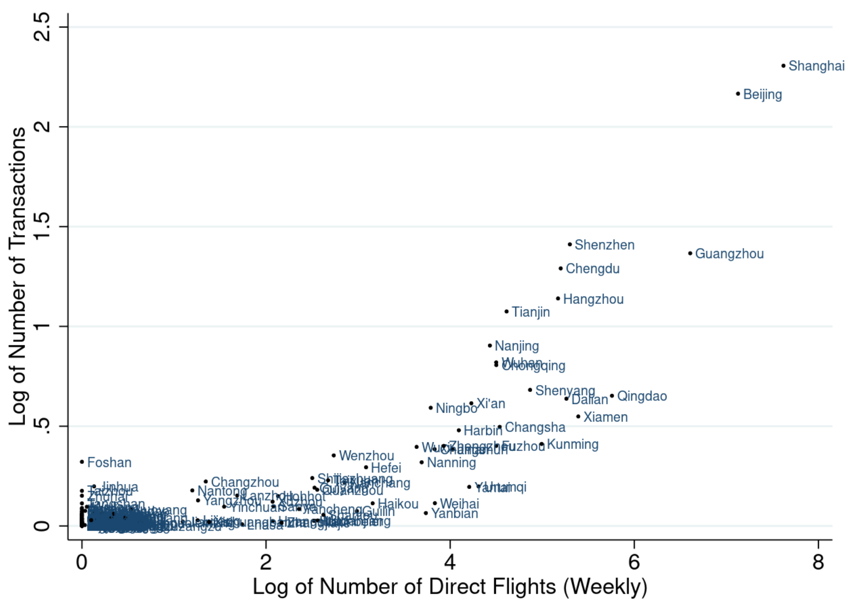
(b) 2016

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 log of transaction values is on the y-axis, and the log of the number of international direct flights (weekly) is on the x-axis. We use the log of the number of transactions on the y-axis in Panel (b).

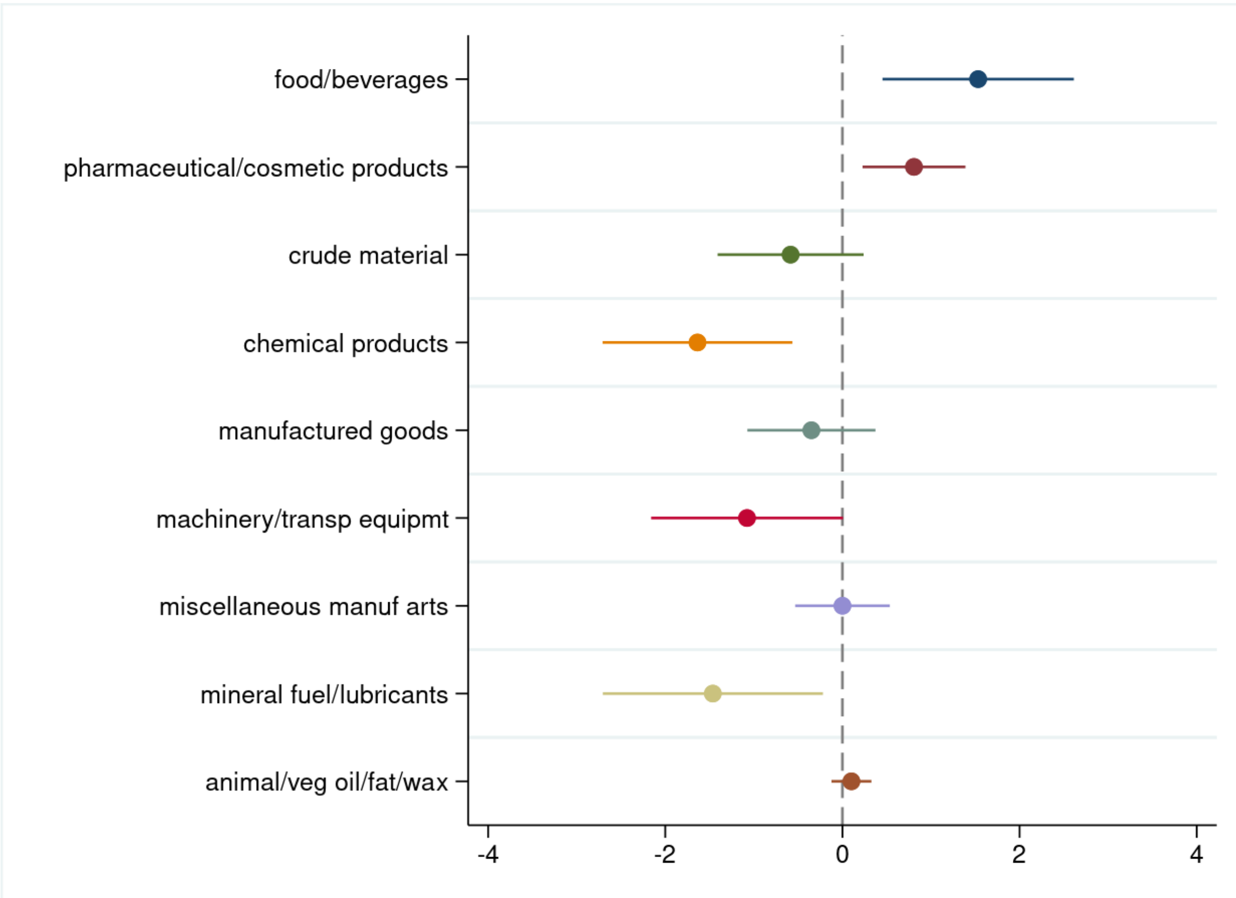


Figure 6: Estimates on Goods Imports by industries

Notes: The figure shows the estimates of air connectivity on goods imports from 2011 to 2016 by industries at the Chinese city-destination country level. Pharmaceutical and cosmetics products are excluded from chemical products.

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	0.71	0	0	896.33	10.60	58,932
Weekly capacity	146.93	0	0	171,321.6	2,181.86	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

Note: We report the mean value, the median value, the minimum and the maximum values, the standard deviations of the variables, and the number of observations.

Table 2: Baseline Results—Effect of Air Connectivity on Cross-border Card Transactions

	log(value)		asinh(value)	log(number)
	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	0.115***	2.284***	2.233***	0.165***
	(0.021)	(0.697)	(0.738)	(0.057)
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
First Stage		log(frequency)		
IV		-17.597***		
		(5.260)		
KP Wald rk F-statistic		11.189		
KP LM statistic		11.776		
KP LM p-value		0.001		
AR Wald test p-value		0.000		

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
[c] OLS: Ordinary least squares; 2SLS: Two-stage least squares; KP: Kleibergen-Paap, AR: Anderson-Rubin
[d] The first stage results in columns (3) and (4) are the same as a result in column (2).

Table 3: Robustness Checks With Different Sample Sizes

	log(card transaction value)			
	Drop Shanghai and Beijing		Add Cities Without Airports	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	0.104***	2.170***	0.105***	4.000***
	(0.020)	(0.627)	(0.022)	(1.429)
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	58,080	58,080	100,380	100,380
First Stage		log(frequency)		log(capacity)
IV		−18.678***		−10.599***
		(5.272)		(3.769)
KP Wald rk F-statistic		12.460		7.909
KP LM statistic		13.135		8.147
KP LM p-value		0.000		0.004
AR Wald test p-value		0.000		0.000

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] $*p < 0.1$, $**p < 0.05$, $***p < 0.01$
[c] OLS: Ordinary least squares; 2SLS: Two-stage least squares; KP: Kleibergen-Paap, AR: Anderson-Rubin

Table 4: Effect of Air Connectivity on Travel to Japan: An Experiment

	log(card transaction value)	
	OLS	2SLS
	(1)	(2)
log(boycott×*injured*)	−0.012***	
	(0.004)	
log(frequency)		1.462**
		(0.619)
Origin city FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	1,152	1,152
First Stage		log(frequency)
log(boycott×*injured*)		−0.005***
		(0.002)
KP Wald rk F-statistic		8.938
KP LM statistic		8.419
KP LM p-value		0.004
AR Wald test p-value		0.003

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] $*p < 0.1$, $**p < 0.05$, $***p < 0.01$
[c] Boycott happened in 2012. We consider boycott as 1 in the year 2012; 0, otherwise.
[d] The variable *injured* measures the number of people injured and dead in each Chinese city during the war with Japan from 1937 to 1945. The data comes from Chi (1987).

Table 5: Effect of Air Connectivity on Goods Imports: 2011-2016

	log(import value)		
	Full Sample	Ordinary Trade	Non-ordinary Trade
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
log(frequency)	−1.092*	−1.449**	−1.135
	(0.643)	(0.673)	(0.714)
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

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$
[c] Goods Trade are in million RMB.
[d] We treat the missing observations in goods trade as zero.

Table 6: Boycott of Philippines, Korea, Japan, and Norway

	log(value)			
	Card transactions	Total imports	Food/Beverages	Phar./cosmetic
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	2.640***	-1.044	0.404	1.325**
	(0.885)	(0.836)	(0.499)	(0.582)
log(frequency)$\times$*boycott*	-0.176***	0.045	0.021	0.041
	(0.057)	(0.045)	(0.031)	(0.039)
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	4,530	4,530	4,530	4,530

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] $*p < 0.1$, $**p < 0.05$, $***p < 0.01$
[c] We use flights to Finland instead of flights to Norway.

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.3, 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	278,584	743,710	465,126	167.0%
United Kingdom	1,237,887	1,513,137	275,250	22.2%
Netherlands	478,979	751,565	272,586	56.9%
Thailand	180,946	411,213	230,267	127.3%
Singapore	241,181	457,399	216,218	89.6%
France	908,909	1,104,703	195,794	21.5%
Spain	684,627	870,389	185,762	27.1%
Japan	305,977	471,428	165,451	54.1%
Italy	623,960	777,392	153,432	24.6%
South Korea	226,749	374,763	148,014	65.3%
Turkey	192,028	339,632	147,604	76.9%
Germany	1,584,126	1,714,556	130,430	8.2%
Saudi Arabia	88,997	192,754	103,757	116.6%
India	173,593	275,614	102,021	58.8%
Malaysia	170,581	263,062	92,481	54.2%
Taiwan	124,749	215,294	90,545	72.6%
Ireland	136,848	215,356	78,508	57.4%
Indonesia	94,552	171,493	76,941	81.4%
Qatar	82,478	156,972	74,494	90.3%
Vietnam	71,855	138,230	66,375	92.4%

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 to the countries in 2011 and 2016, respectively. The fourth column shows the change in total inbound flights from 2011 to 2016. The last column reports the percentage change in inbound flights in each country.