Air Connectivity and Cross-border Travel*

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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 2.6% increase in cross-border card transaction value. We also find that the improvement in bilateral air connectivity diverts travelers away from surrounding countries. Our results reveal the complexities involved in evaluating the benefits of public investment in air travel infrastructure.

Keywords: Air Transportation, Trade in Tourism and Travel-related Services, and Travel 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 2.6% increase in the value of card transactions in the destination country. This result is robust to different specifications and sample restrictions. We also find that new air connections increase the value of transactions in the country connected by direct flights, while decreasing the value in surrounding countries (i.e., diversion effects). In particular, a 1% increase in air connectivity in the closest country decreases the value of transactions by 0.14%.

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

[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.

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.

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 baseline results in Section 5, and show the analysis of the diversion of travel destinations in Section 6. Section 7 concludes.

2 Data and Stylized Facts

We use a unique dataset of Chinese card transactions made in foreign countries. We merge the casrd transaction data with worldwide international flight schedules to analyze the effect of air connectivity on Chinese overseas travel spending. We also introduce the three stylized facts that we observe in our novel data.

2.1 Data Sources

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

[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.

from a consumer card provider in China. The data comes from the transactions that Chinese cardholders make outside China.[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. 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.[7]

The air connectivity data comes from OAG Analyser. This database provides worldwide 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 destination country. We define frequency (or capacity, in terms of 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.[8]

Next, we merge the two main datasets, the Chinese card transaction data and the flight data. In the final dataset, we observe 190 unique Chinese cities (origins) and 72 unique foreign countries (destinations), with a total of 58,734 origin-destination pairs.[9] The destination

[5]The data exclude online transactions.

[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.

[7]*Payment methods report 2019* on page 21, Link to the report (last access on November 6, 2022)

[8]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).

[9]We focus on the cities in mainland China. There are 336 Chinese cities in the card transaction data,

countries are listed in Table A.1.

2.2 Descriptive Statistics

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 9.4 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.

On average, each origin city-destination country pair has 0.72 weekly flights, with just over 148 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.

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

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.

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.[10]

[10] 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 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 $X_i = \beta_i Y_i$ 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[11]:

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

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

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

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

where 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 transaction 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).[12] We include city-country fixed effects, δ_{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, 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

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

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 greater demand for travel services and higher levels 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 Testing for Potential Reverse Causality

We test for reverse causality by adding a set of variables that capture the future air connectivity (i.e., Granger causality testing). If air connectivity affects the value of transactions but not vice versa, only future connectivity cannot predict the value of transactions. Specifically, we run the regression:

$$\ln X_{ijt} = \alpha + \sum_{\tau=1}^{4} \beta_\tau \ln D_{ij,t+\tau} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}. \tag{6}$$

In the equation above, we include three leads ($\beta_2 \ln D_2$, $\beta_3 \ln D_3$, and $\beta_4 \ln D_4$) to equation (5). If air connectivity is exogenous with respect to cross-border travel, the null hypothesis that $\beta_2 = \beta_3 = \beta_4 = 0$ should not be rejected.

4.2.2 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

$$Z_{ijt} = \lambda_{jt} \times \ln dist_{ij}, \tag{7}$$

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.[13] 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 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.[14] We assume that distance affects our dependent variable (value of card transactions) only through air connectivity (our endogenous variable).[15] 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.

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

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

[14] 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).

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

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).[16] 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.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 164% 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:

$$\begin{aligned} \ln D_{ijt} &= \gamma + \beta_0 Z_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \xi_{ijt} && \text{(first stage)} \\ \ln X_{ijt} &= \alpha + \beta_1 \ln D_{ijt} + \delta_{ij} + \eta_{it} + \kappa_{jt} + \epsilon_{ijt}. && \text{(second stage)}, \end{aligned}$$

where we define Z_{ijt} in equation 7. 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

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

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 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

Table 2 shows the effects 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 of 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.

As discussed in 4.2.1, we regress equation (6) which tests the "strict exogeneity" of the weekly number of flights by adding lead air connectivity into our empirical model. Column 2 reports the results. The coefficients of some of the lead values are all positive and significant. An unobserved contemporaneous shock to cross-border travel spending induces a positive response to air connectivity. This result suggests that there might be reverse causality.

The result of IV estimation is in column 3. We report the first-stage results at the bottom of the table. The coefficient of IV is negative and highly significant. More importantly, the first-stage F statistic is 11.29, which suggests that we can reject the null of the weak instrument.[17] The second-stage results find that a 1% increase in the weekly frequency of direct flights leads to a 2.6% increase in cross-border card transaction value.

Additionally, the IV coefficient is larger than the OLS coefficient reported in column 1. This downward bias is inconsistent with a reverse causality argument, that air connectivity

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

responds to existing demand for travel services. Rather, this pattern underscores differences 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 7).

We apply the inverse hyperbolic sine (IHS) transformation to the value of transactions because Table 1 documents that there is a non-trivial fraction of zero values.[18] The IHS function can approximate the natural logarithm of the variable and allow the retaining of zero-valued observations (Bellemare and Wichman 2020). The result is in column 4 of Table 2. Encouragingly, the coefficient is very similar to the one in column 3 in terms of size, significance, and sign.

5.2 Robustness Checks

Our IV regressions show that the 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) and air connectivity (i.e., independent variable). We also change our specifications to select our sample for further robustness checks.

[18] We also employ the Poisson Pseudo-Maximum-Likelihood (PPLM) method to test if the estimate using PPML is similar to the one in our OLS result (column 1). The advantages of the PPML method are that it accounts for heteroskedasticity (Santos Silva and Tenreyro 2006), and ensures that the gravity-fixed effects are identical to their corresponding structural terms (Arvis and Shepherd 2013). The result with PPML is very similar to the OLS result.

5.2.1 Alternative Variables

One of the robustness checks is to employ an alternative dependent variable. In particular, 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 0.14% increase in the number of card transactions. The positive and statistically significant result is similar to the result using the value of transactions (in column 3 of Table 2). We obtain a similar result using the inverse hyperbolic sine (IHS) transformation (Column 2 of Table 3).

Alternatively, we employ an alternative measure of air connectivity (i.e., a different dependent variable). More specifically, we replace the weekly frequency of direct flights with the weekly capacity of direct flights. We measure the capacity using the number of seats in air plains. Column 3 of Table 3 shows the result with flight capacity as a dependent variable and the value of card consumption as an independent variable. Column 4 of Table 3 reports the result using the number of card transactions as an alternative independent variable. Similar to the main results (columns 3 of Table 2), we observe the positive and significant coefficients.

5.2.2 Different Sample Sizes

We limit and expand our sample size to check if the results with different specifications are similar to the baseline results (shown in column 3 of Table 2). The potential issue we stated in Section 2.3 is that most of the Chinese travelers are from Shanghai and Beijing, and therefore our estimate may be largely driven by the travelers from these two cities. We drop the observations with Shanghai and Beijing and run regressions to test whether our findings are still robust using the restricted sample. Columns 1 and 2 of Table 4 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 cities; rather, they represent all Chinese cities with airports.

We also try to expand our scope to select Chinese cities in our sample. We so far focus on the cities that have airports during our sample period and analyze the effect of the number of weekly direct flights on overseas travel spending. There are two groups of cities in our sample: one is the cities that do not have direct flights to a foreign country, and the other is the cities that have direct flights to a foreign country before our sample period.[19] Here, we include the additional group of Chinese cities—cities that do not have airports. Residents in those cities do not have access to domestic flights. If we include those cities in our sample, we expect that the size of the coefficient of interest would be larger than that in our main result because our baseline group would be cities without access to air transportation, instead of cities without access to international flights. The results are in columns 3 and 4 of Table 4. The coefficient of the 2SLS estimate is positive and significant, and as expected, the size is larger than the coefficient in our main result (column 3 of Table 3).

6 Extension: Trade Diversion

An increase in air connectivity means a decrease in trade costs. In the field of international trade, one of the major events to reduce trade costs is a regional trade agreement. The regional trade agreement increases trade between member countries in two ways. One is that a member country starts importing a product from another member country instead of producing for itself (i.e., trade creation). The other is that a member country starts importing a good from another member country, and that good is previously imported from a country outside the trade agreement (i.e., trade diversion). In our setting, the former is the case that a Chinese consumer who does not travel before starts traveling overseas because of the increase in air connectivity. The latter is the situation where a Chinese consumer changes their destination to a country with easier access from another country. We test the latter diversion effect in this section.

To test whether travelers divert destinations because of more direct flights, we add the weekly frequency of the direct flights to the first closest countries to the destination as additional independent variables into the main regression (equation 5).[20] The transactions

[19]This implies that our estimates include the effect of extensive margin (by having new direct flights) and that of intensive margin (by a rise in the number of weekly direct flights).

[20]We refer to the empirical strategy in Dai, Yotov, and Zylkin (2014) who study the diversion effects of free trade agreements.

in a destination, log(value), can be negatively affected by the air connectivity in the first closest destinations, log(frequency-1st-closest-country). If there is a diversion effect, we observe the negative and significant coefficients on these two frequency variables.

The results are presented in Table 5. Column 1 shows the diversion effects toward the most closet destination. It indicates that a 1% increase in frequency in the closest country leads to around 0.14% decrease in travel to that destination. We take an average of the number of direct flights for the first and second closest countries and reexamine the diversion effect. The result in column 2 indicates that a 1% increase in the average frequency in the closest two countries decreases the value of card transactions by 0.33%. For robustness, we check the diversion effects using the average frequency of the closest 4 countries and 6 countries, respectively, and the results are in columns 3 and 4. The significant and negative coefficients on the two average frequencies underline the existence of the diversion effects.

7 Conclusion

This paper studies the effect of air connectivity on cross-border travel. Our unique data allow us to observe the value of card transactions from Chinese cities to foreign countries. We construct a Bartik-style IV that gives us variations uncorrelated to transitory shock at the city-foreign country level. Our 2SLS estimates indicate that a 1% increase in the weekly frequency of direct flights leads to a 2.6% increase in the value of transactions. Our results are robust with alternative variables and sample sizes. We also find that improvement in air connectivity decreases the value of transactions in adjacent countries (i.e., diversion effects).

Improvement in air connectivity reduces travel costs and thus encourages more Chinese consumers to travel overseas. Our study proves that relationship, but moreover, our unique Chinese city-foreign country level data enable us to test the diversion effects in terms of the improvement in air connectivity. This gives a lesson for policymakers who consider establishing air connections with foreign countries to promote the cross-border travel of their residents. We find that several air connections to nearby destinations divert cross-border travel from one destination to another. Therefore, such diversion should be taken into account when policymakers plan to expand air connectivity to foreign countries.

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Figures

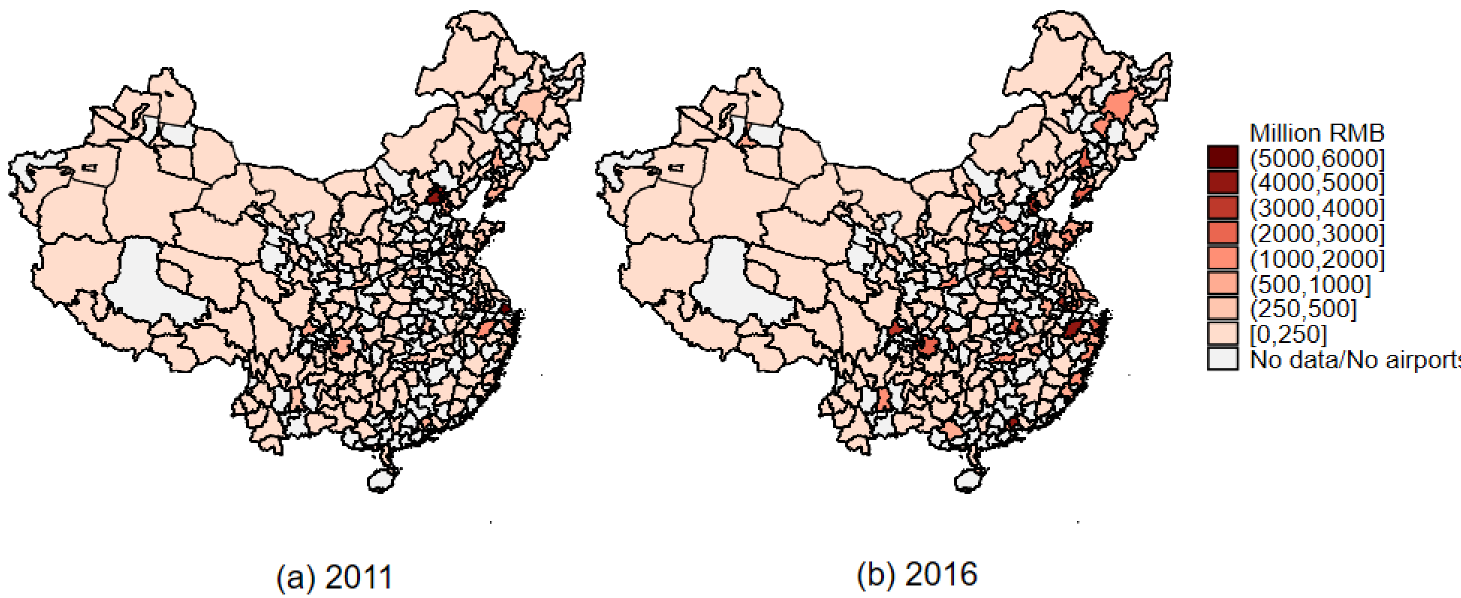


Figure 1: Chinese Cities With Overseas Transaction Values in 2011 and 2016

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.

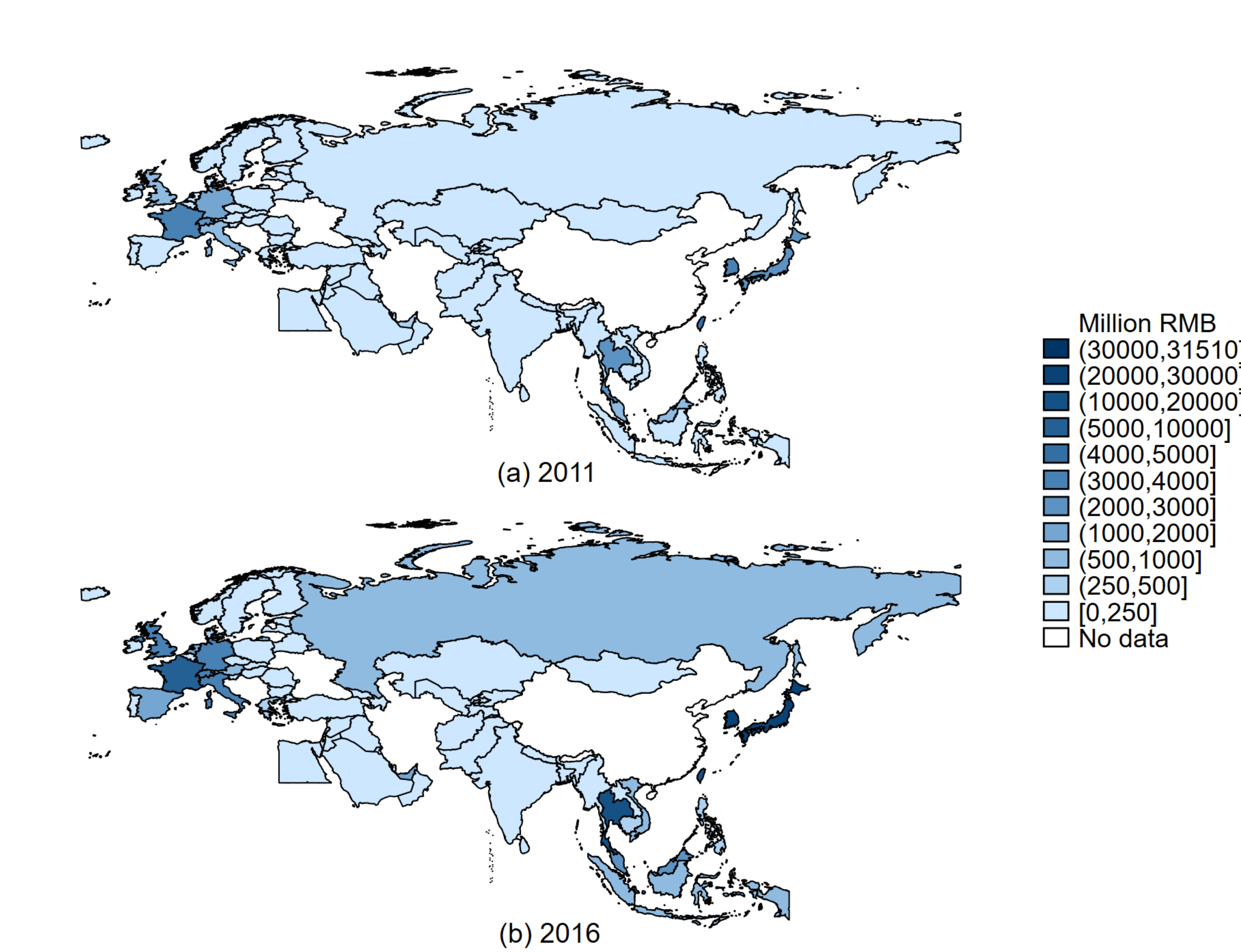
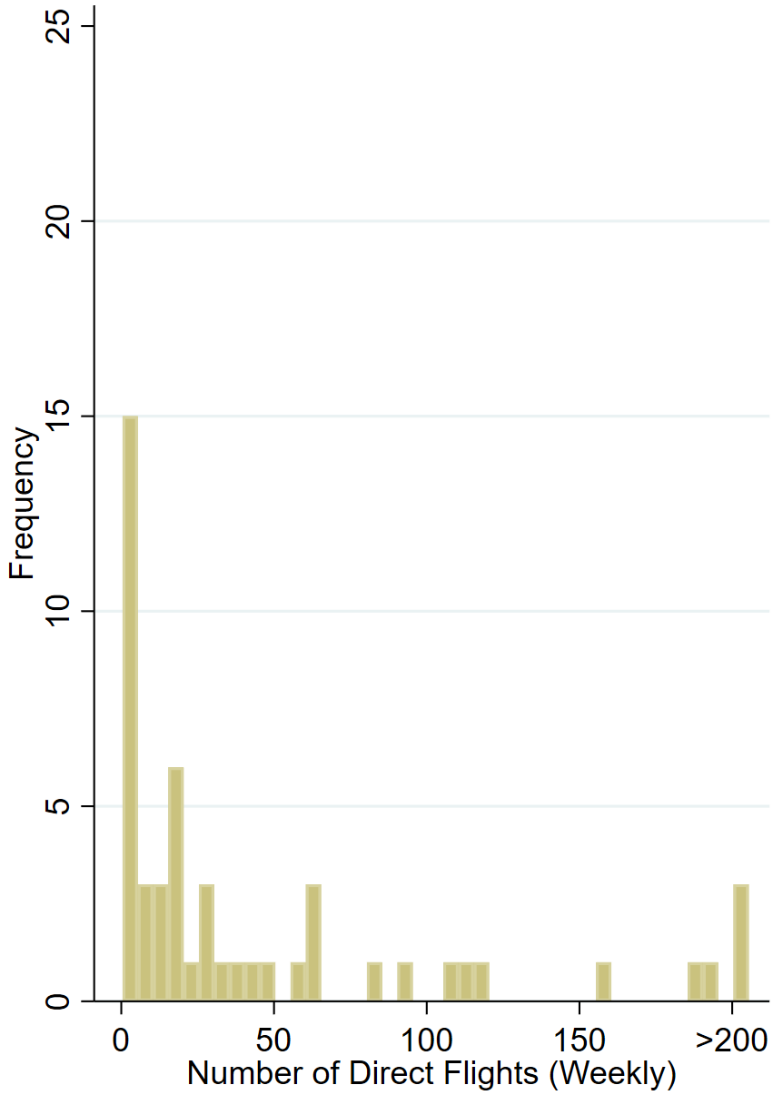
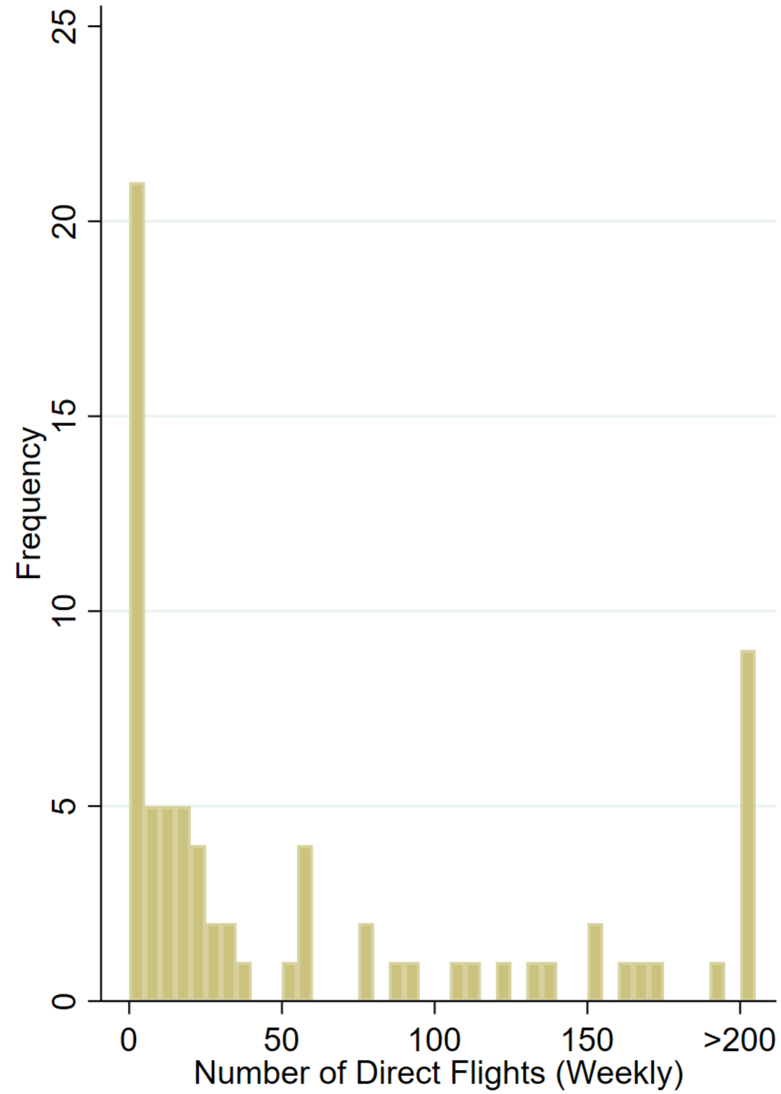


Figure 2: Travel Destinations With Card Transaction Values in 2011 and 2016

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.



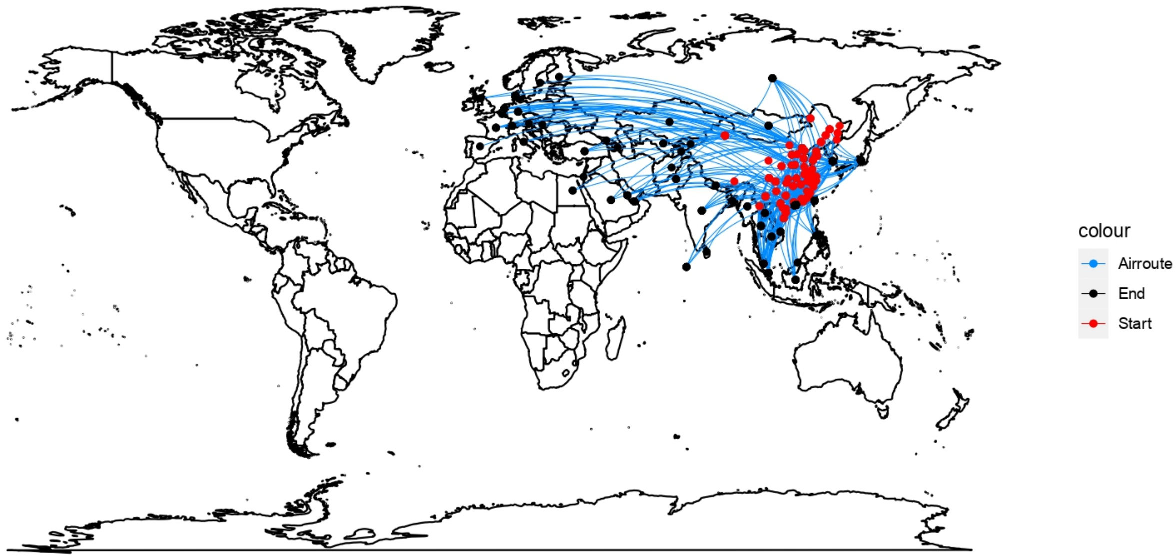
(a) 2011



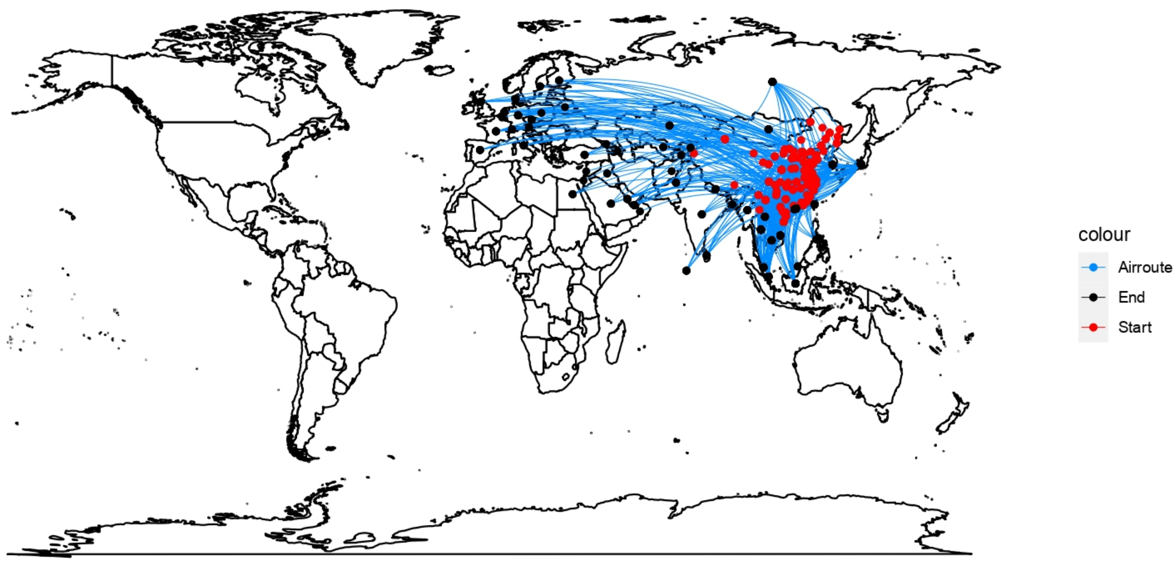
(b) 2016

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.



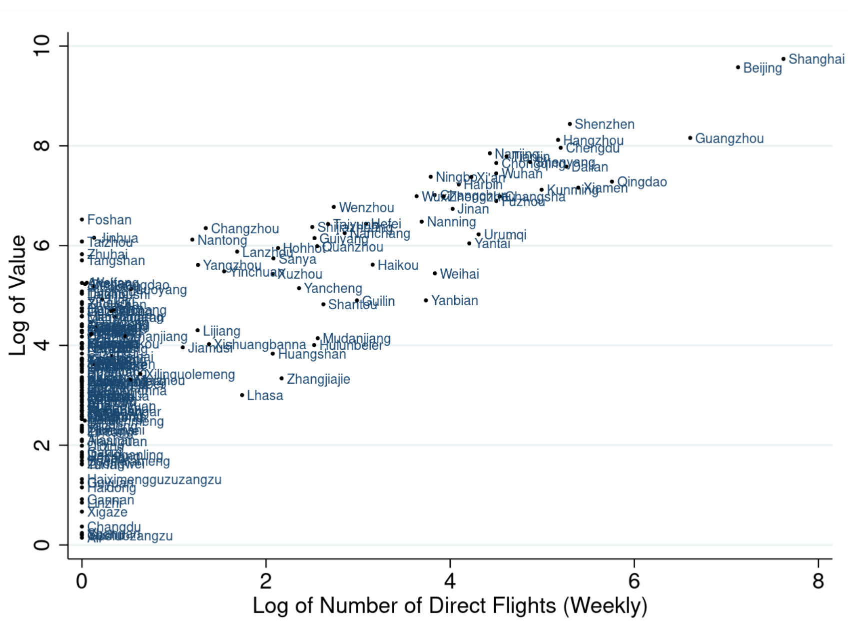
(a) 2011



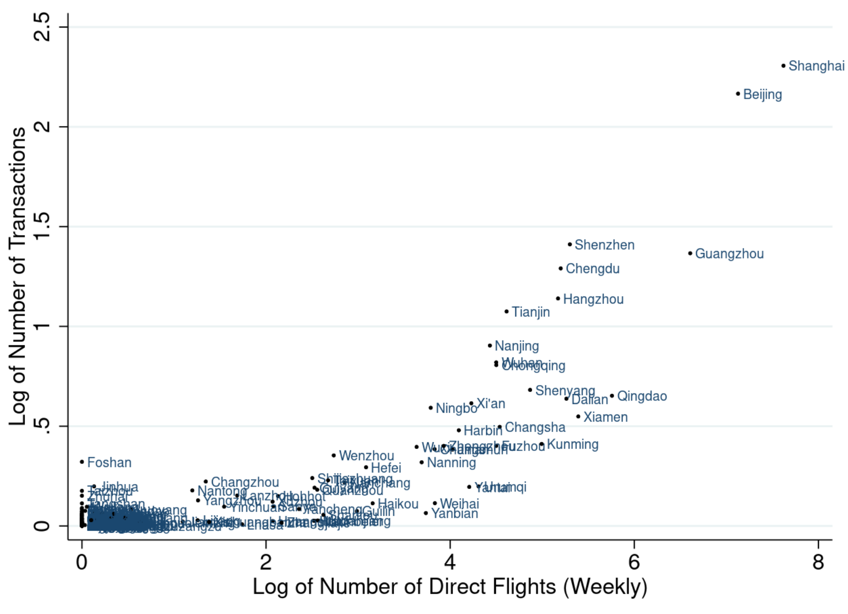
(b) 2016

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) on the x-axis. We use the log of the number of transactions on the y-axis in Panel (b).

Tables

Table 1: Summary Statistics

Variables	Mean	P(50)	Min	Max	SD	Mean (Value $\geq$ P(75))
Card transaction data						
Value (millions RMB)	9.41	0.036	0	9,626.68	100.03	37.41
Number of transactions	5,294.85	16.00	0	5,399,033	78,900.21	21,042.33
Direct flight data						
Weekly frequency	0.72	0	0	896.33	10.65	2.83
Weekly capacity	148.34	0	0	171,321.6	2,192.21	584.53
Observations	58,374					14,593

Note: We report the mean value, the median value, the minimum and the maximum values, and the standard deviations of the variables. We limit the sample with the value of card transactions above and equal to the 75th percentile and report the mean value of each variable in the last column.

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

	log(value)			asinh(value)
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	0.115***	0.076***	2.598***	2.614***
	(0.021)	(0.021)	(0.770)	(0.828)
log(frequency)(t+1)		0.039**		
		(0.016)		
log(frequency)(t+2)		0.019		
		(0.013)		
log(frequency)(t+3)		0.064***		
		(0.014)		
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	58,374	58,374	58,374	58,374
First Stage			log(frequency)	log(frequency)
IV			−16.136***	−16.136***
			(4.802)	(4.802)
KP Wald rk F-statistic			11.290	11.290
KP LM statistic			11.909	11.909
KP LM p-value			0.001	0.001
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 3: Robustness Checks With Number of Transaction and Weekly Capacity

	log(number) 2SLS (1)	asinh(number) 2SLS (2)	log(value) 2SLS (3)	log(number) 2SLS (4)
log(frequency)	0.139**	0.162***		
	(0.054)	(0.068)		
log(capacity)			1.108**	0.059**
			(0.440)	(0.029)
City-Year FEs	Yes	Yes	Yes	Yes
Country-Year FEs	Yes	Yes	Yes	Yes
City-country FEs	Yes	Yes	Yes	Yes
Observations	58,374	58,374	58,374	58,374
First Stage	log(frequency)	log(frequency)	log(capacity)	log(capacity)
IV	−16.136***	−16.136***	−37.838**	−37.838**
	(4.802)	(4.802)	(15.309)	(15.309)
KP Wald rk F-statistic	11.290	11.290	6.109	6.109
KP LM statistic	11.909	11.909	6.365	6.365
KP LM p-value	0.001	0.001	0.012	0.012
AR Wald test p-value	0.000	0.000	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] Pseudo R-squared in column 2 is 0.980.

[d] 2SLS: Two-stage least squares; KP: Kleibergen-Paap, AR: Anderson-Rubin

Table 4: Robustness Checks With Different Sample Sizes

	Drop Shanghai and Beijing		Add Cities Without Airports	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	0.104***	2.443***	0.105***	4.389***
	(0.020)	(0.677)	(0.022)	(1.513)
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	57,522	57,522	100,116	100,116
First Stage		log(frequency)		log(capacity)
IV		−17.295***		−10.073**
		(4.807)		(3.514)
KP Wald rk F-statistic		12.944		8.214
KP LM statistic		13.695		8.467
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 5: Diversion Effect: Number of Direct Flights

	log(value)			
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
log(frequency)	2.672***	2.837***	2.889***	2.872***
	(0.826)	(0.918)	(0.953)	(0.935)
log(frequency-1st-closest-country)	−0.139*			
	(0.081)			
log(frequency) average-2-closest-countries		−0.328***		
		(0.126)		
log(frequency) average-4-closest-countries			−0.409**	
			(0.164)	
log(frequency) average-6-closest-countries				−0.447***
				(0.168)
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	58,374	58,374	58,374	58,374

[a] Standard errors, clustered at the city-country level, are in parentheses.
[b] $*p < 0.1$, $**p < 0.05$, $***p < 0.01$
[c] 2SLS: Two-stage least squares
[d] log(frequency-1st-closest-country) is the number of direct flights to the country with its capital city that is the closest to the destination country; log(frequency) average-2-closest-countries is the average number of flights of the 1st and 2nd closest countries; log(frequency) average-4-closest-countries represents the average number of flights of the first four closest countries; log(frequency) average-6-closest-countries represents the average number of flights of the first six closest countries.

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 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	95,301	246,665	151,364	158.8%
United Kingdom	404,840	500,215	95,375	23.6%
Netherlands	158,414	249,220	90,806	57.3%
Thailand	60,907	135,960	75,053	123.2%
Singapore	85422	155,219	69,797	81.7%
France	300,231	361,854	61,623	20.5%
Japan	101,632	161,957	60,325	59.4%
Spain	226,716	286,294	59,578	26.3%
Turkey	62,556	115,565	53,009	84.7%
South Korea	74,772	122,022	47,250	63.2%
Italy	211,569	253,063	41,494	19.6%
India	58,653	95,136	36,483	62.2%
Malaysia	54,958	89,391	34,433	62.7%
Saudi Arabia	31,495	61,457	29,962	95.1%
Taiwan	40,538	68,385	27847	68.7%
Qatar	28,103	54,796	26,693	95.0%
Indonesia	31,924	57,852	25,928	81.2%
Ireland	46,943	68,722	21,779	46.4%
Vietnam	27,504	46,963	19,459	70.7%
Germany	529,949	548,337	18,388	3.5%

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.