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

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Abstract

We investigate the impact of direct flight connections on international travel, the largest tradable service sector. A novel dataset on card payments made by Chinese travelers through point-of-sale (POS) terminals enables us to analyze the bilateral flow of international travel. We instrument for the frequency of direct flights between Chinese cities and foreign countries by exploiting overseas airport expansions as exogenous shocks. Our IV estimates indicate that a 1% increase in the weekly frequency of direct flights leads to a 1.8% increase in cross-border card transaction value. This suggests that in a city with the average weekly frequency, one additional direct flight increases the value of transactions by 48.53% to the destination country. While improving air connectivity promotes international travel, we find that negative shocks to consumer preferences for destination countries, such as boycotts, diminish this effect.

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

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1 Introduction

International travel, such as tourism and business trips, accounts for a quarter of overall traded services, significantly contributing to the global economy.[1] For example, international tourism ranks as the world's third-largest export category, following fuels and chemicals, and surpassing automotive products and food (UNWTO 2021). Given its importance, policymakers are actively involved in the development of their travel and tourism sectors, including investments in air transportation infrastructure and the expansion of air connectivity. However, despite the economic significance of international travel, there is limited evidence on how the development of air transportation promotes international travel, which hinders the evaluation of related policy initiatives. This paper addresses this gap and presents the first attempt to examine the effect of air connectivity on trade in travel services.

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

We develop a gravity-type model to explain the bilateral flow of trade in travel service, following Head et al. (2008) and Farber and Gaubert (2019). Our model accounts for consumer decision-making when choosing among various travel destinations, with the attractiveness of foreign destinations and travel costs (i.e., air connectivity). We derive a gravity equation from the model, which enables us to identify the effects of air connectivity on international travel with three-way fixed effects (FEs): Chinese city-foreign country, Chinese city-time, and foreign country-time FEs.

[1] For instance, international tourism has steadily grown for over six decades, contributing, on average, 4.4% to GDP of OECD countries (OECD 2020).

A potential threat to identification is the reverse causality from cross-border travel to air connectivity: when demand for travel from a Chinese city to a particular country increases, airlines are more likely to connect to that city-country pair with a direct flight. To address this concern, we instrument for air connectivity using overseas airport expansions as exogenous shocks. In particular, our instrument is the share of global flights departing in the destination country (representing that country's comparative advantage in air transportation) combined with the geographic distance between a Chinese city-foreign country pair (distant locations are less connected by flights; Cristea 2023). Our instrument is similar to shift-share instruments (Bartik 1991). The main identifying assumption is that investment in air flight capacity made by foreign governments is uncorrelated with demand shocks for Chinese travelers to that country.

Our IV estimate indicates that a 1% increase in the weekly frequency of direct flights leads to a 1.82% increase in the value of card transactions in the destination country. This suggests that if a city with the average frequency of direct flights receives one additional direct flight per week, travelers make 48.53% more card payments in that destination country. We observe a similar impact of direct flights using travel time as an alternative measure of air connectivity. The positive impact of the improvement in air transportation on card transaction values is robust to different specifications, such as excluding Beijing and Shanghai and considering the possibility of traveling to nearby airports located in other cities.

Improvement in air connectivity not only impacts trade in travel services but also influences trade in goods. For instance, passenger planes transport air freight, and consumers who experience new products in their travel abroad may develop a preference for those items, leading to more imports. Building on this premise, we further analyze how improvements in air connectivity affect Chinese imports using customs data. We find that a higher frequency of weekly direct flights increases the value of imported consumer products that are typically transported by air, such as food and pharmaceuticals.

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

China presents a useful case study for understanding the relationship between air connectivity and trade in travel services. China has made the largest amount of spending on international travel, accounting for one-fifth of global travel spending, followed by the US (UNWTO 2021). Moreover, not only is there a large demand for international travel, but the Chinese aviation network has also dramatically developed, making China the world's second-largest air transportation market since 2013 (Gibbons and Wu 2020). For example, the number of foreign countries connected with Chinese cities by air increased by around 70% from 2000 to 2016.[2] These rapid expansions of cross-border travel and air connectivity provide meaningful variation for our estimation.

This paper contributes to the literature that studies the effects of international air transportation on economic development (Hovhannisyan and Keller 2015; Campante and Yanagizawa-Drott 2017; Cristea 2023), international trade (Cristea 2011; Alderighi and Gaggero 2017; Wang et al. 2021; Söderlund 2022), foreign investment (Campante and Yanagizawa-Drott 2017; Fageda 2017; Tanaka 2019), and cross-border mergers and acquisitions (Zhang et al. 2021). Although cross-border travel is a major part of international trade, there is no study examining how air transportation affects cross-border travel, and how such effect is different from that on trade in goods. Our work extends the literature by looking into the effects of international air transportation on trade in services and goods, and shows their asymmetric responses to facilitation in international airport transportation. Further, we extend the literature by exploiting a novel identification strategy to estimate the causal impact of air connectivity on trade in services and goods. Specifically, we exploit variations

[2]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.

in overseas airport expansions as exogenous shocks to the air connectivity between Chinese cities and foreign countries.

Our study is also related to the literature on cross-border travel, which identifies various determinants for consumers traveling to shop in another country.[3] Asplund et al. (2007) and Friberg et al. (2022) use data of Sweden and Denmark, while Chandra et al. (2014) and Baggs et al. (2018) look into cross-border travel between Canada and the US. Since Canada and the US are similar to each other in various aspects, thus the previous studies focus on the effects of price differential and travel costs (proxied by distance) on cross-border travel.[4] In contrast, we study cross-border travel between non-contiguous countries, which has been becoming more common as air transportation becomes more affordable. Our setting also contains a large set of destination countries, allowing us to study how consumer sentiment towards another country affects cross-border travel.

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

2 Data and Stylized Facts

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

[3]Another strand of the literature concerning cross-border travel investigates the welfare impact of tourism on local residents. For example, Allen et al. (2021) use card transaction data in the city of Barcelona, and Faber and Gaubert (2018) focus on the welfare of Mexican locals using micro datasets. In contrast to these studies, our research examines the imports of travel services (i.e., Chinese consumers traveling abroad) instead of the exports (i.e., foreign travelers consuming local goods and services in destination countries).

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

2.1 Data Sources

(i) Chinese overseas card transactions

A unique dataset of Chinese on-site card transactions enables us to analyze the spending by Chinese travelers overseas. We collect a dataset on card transactions between 2011 and 2016 from a Chinese consumer card provider. The data include transactions made by Chinese cardholders outside China through POS terminals, excluding online transactions.[5] For confidentiality reasons, our data provider aggregates the data at the city of residence-destination country-year level. We observe the value and number of transactions by cardholders' cities of residence and countries where the transactions were made.[6] Our data include 72 destination countries in Europe and Asia that contribute to 64% of global exports in trade in travel services (excluding export from China).[7] The destination countries are listed in Table A.1.

(ii) Global flight schedules

Our air connectivity data comes from OAG Analyser, which provides worldwide flight schedules. This dataset includes the name of the departure and arrival airports, departure and arrival time, elapsed time, travel distance, and the number of stops, covering the period from 2011 to 2016. We add the names of Chinese cities served by airports, and latitudes and longitudes of destination countries and Chinese cities. Our primary measure of air connectivity is the weekly frequency of direct flights between a Chinese city and a destination country. We also calculate the travel time from a Chinese city to a foreign country as an alternative measure. Unlike the weekly frequency of direct flights, we consider indirect flight routes with up to two domestic flight connections, adding a three-hour connecting time at each layover airport.[8] Appendix Section B provides a detailed explanation of how we construct the measure of air connectivity.

[5]Our data contains the transactions made with cards issued by domestic card brands, excluding foreign brands such as Visa and Mastercard. This limitation does not bias our analyses as the vast majority of Chinese residents use cards issued by Chinese brands (e.g., 99% of card payments in China). Reference: *Global Payments Report 2023*, page 48, link to the report (last access on January 21, 2023).

[6]The data provider imputes cities of residence using past card transactions, assuming that a cardholder lives in the city with the highest number of transactions.

[7]We calculate this number using the WTO trade in services annual dataset.

[8]If there are multiple fight routes from a Chinese city to a foreign country, we pick the route with the shortest duration.

(iii) Chinese import data

Chinese import data are collected by China's General Administration of Customs (CGAC) for the period of 2011-2016. For each import transaction, we observe the company name, company code, city of the company's location, product name, HS 8-digit product code, country of origin, time (year and month), and transaction value.[9] We classify the imported products into consumer and non-consumer goods using the classification provided by the UNCTAD.

2.2 Descriptive Statistics

We merge the two main datasets, the Chinese card transaction data and the flight data. The final dataset includes 192 unique Chinese cities (origins) and 72 unique foreign countries (destinations), resulting in a total of 58,932 origin-destination pairs.[10] Our data contain the Chinese cities with airports and positive transaction values for at least a year over our data period.

Table 1 presents the descriptive statistics of our estimation sample. 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 from an origin city spend 9.3 million Renminbi (RMB) and conduct around 5,000 card transactions in a foreign country per year. The distributions of the value and the number of transactions are skewed to the right since the mean value is larger than the median value. Similar to the transaction value and number, the distribution of the weekly frequency is also right-skewed because some cities have larger airports that attract more direct flights. On average, there are 0.45 direct flights per week on each flight route, with a travel time of 13.39 hours.

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

[10] 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.

2.3 Stylized Facts

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

Fact 1: Regional differences in transaction value

First, we focus on the card transaction data and analyze the increase in the value of transactions between 2011 and 2016. Figure 1 shows the change in the total value of transactions on a map of mainland China from 2011 to 2016, highlighting the variation across origin cities. We observe an increase in the value of transactions in all Chinese cities in our sample, particularly in 22 cities where the card transaction value increased by more than one billion RMB. The cities that experienced the largest growth are Shanghai (328% increase), Beijing (289% increase), and Guangdong (375% increase). Interestingly, the large growth of the transaction values is observed not only in the cities in Eastern China but also in inland regions such as Chengdu, Wuhan, and Chongqing. For example, total overseas transactions in Wuhan (an inland city in Hubei Province) increased by around 421%, from 441 million to over 2.3 billion RMB.

We also map the change in the total value of transactions across destination countries (Figure 2). All countries received more value of transactions in 2016 than in 2011. The countries with the most substantial increase in card transaction value are Japan (26.2 billion RMB), Korea (20.1 billion RMB), and Thailand (11.1 billion RMB). We observe a significant rise in transactions even in countries farther from China. For example, 14 countries experienced growth of more than one billion RMB, and seven of them are in Europe, including the UK, France, Italy, and Germany.

Fact 2: Improvement in air connectivity

We measure air connectivity using the weekly frequency of direct flights (i.e., the number of direct flights per week) at the city-country-year level. The improvement in air connectivity affects spending by Chinese travelers in two ways: (i) more frequent international direct flights on existing flight routes (i.e., intensive-margin effect), and (ii) the opening of new direct flight routes (i.e., extensive-margin effect).[11]

To analyze the intensive-margin effect, we restrict our sample to flight routes that exist in 2011, and compare the average weekly frequency at the city level between 2011 and 2016. Figure 3 shows the distribution of the increase in average frequency in 2016 compared to 2011. There are 52 cities with at least one international flight route in 2011. On average, airlines operate an additional 6.25 flights per week on existing air routes in 2016. In particular, air connectivity in Qingdao has dramatically improved through the intensive-margin effect, with an average increase of more than 25.55 flights per week in 2016 compared to 2011.[12]

For the extensive-margin effect, we illustrate the new direct flight routes that opened over our data period. Between 2011 and 2016, there were 272 new direct flight routes, and Chinese cities were connected with 1.42 new destinations on average. Among the 73 cities with at least one new flight route, Chengdu attracted the largest number of new routes as it was newly connected with 14 countries in 2016 compared to 2011. The most frequent direct flight route from Chengdu is bound for Vietnam, with a 21.10 weekly frequency in 2016. Additionally, Thailand attracted the largest number of new routes, which are connected with 39 cities.

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

We first calculate the average values of transactions and the weekly frequency of direct flights at the city-year level, and take the difference between 2011 and 2016. We then plot the difference in the average transaction values on the x-axis and that in the average of the weekly frequency on the y-axis (Figure 5). In Panel (a), we observe a positive correlation, which suggests that Chinese travelers in cities with an improvement in air connectivity spent more overseas. We observe that major cities such as Shanghai, Beijing, and Guangzhou experienced a larger increase both in air connectivity and transaction value. Even when we exclude these three cities, a positive relationship between air connectivity and card transac-

[11] Flight routes are defined at the city-country level.

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

tion values persists (Panel (b)).[13] We find a similar positive correlation using the number of transactions, instead of the value (Appendix Figure A.1). In the subsequent sections, we empirically investigate these positive relationships.

3 Model and Empirical Strategy

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

3.1 Model

Our model is based on Head et al. (2008), who introduce a model for bilateral service trade to derive a gravity-type equation for trade in the travel service sector. 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 trade in travel services.

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

[13] For a robustness check, we exclude the transactions from Shanghai and Beijing in our data, and run a regression. We obtain a result almost identical to the main regression. Please refer to Section 4.1 for details.

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 visits there to consume travel-related services.

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

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

where a_j is the amenity that each destination provides to a consumer, q_{ij} is the quantity of travel services, and 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:

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

Tourism Service Technology:

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

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

where A_j is a country-specific attractiveness as a travel destination, and 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 et al. (1992, p.39), the choice probability takes the multinomial logit formula[14]:

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

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.

Bilateral Flow of Trade in Travel Services:

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

Air Connectivity:

There are two types of costs for consumers to travel to their destination countries: one is

[14] 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

time-varying—the degree of air flight connectivity between Chinese city i and foreign country j—while the other is time-invariant—characteristics that are common to i and j, such as language barriers. We can express the total trade costs, 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 the variables in 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 flow of travel services in year t depends on effects specific to Chinese city i, effects specific to foreign destination j, and the origin-destination effects of travel costs.

3.2 Model Implementation: OLS Estimation

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

A notable challenge in our data is the presence of substantial zero values in transaction values X_{ijt} and weekly frequency of direct flights D_{ijt}. We apply the inverse hyperbolic sine (or arcsinh) transformation to both variables to address this issue.[15] This transformation approximates the natural logarithm of the variables while allowing for zero observations.

[15]The formula for the inverse hyperbolic sine transformation is $\tilde{x} = arcsinh(x) = \ln(x + \sqrt{x^2+1})$. Alternatively, we could employ the Poisson Pseudo Maximum Likelihood (PPML) regression to address zero values. See footnote 25 for further details.

Our baseline regression specification is

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

where $\tilde{X}_{ijt}$ denotes the value of total card transactions by Chinese travelers from city i in country j, and $\tilde{D}_{ijt}$ is the level of air connectivity (i.e., weekly frequency of direct flights between i and j). The inverse hyperbolic sine transformation has been applied to both variables. The estimated coefficient can be approximated to the elasticity, which is the ratio between the percentage change in the transaction value and the corresponding percentage change in the weekly frequency of direct flights (Bellemare and Wichman 2022).[16]

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 factors, such as tourist attractions and the price of travel services.

Based on our descriptive analysis in Section 2.3, we expect that the improvement in air connectivity will increase the number of travelers, and thus the value of card transactions will rise as well. In other words, we expect the coefficient of interest, γ_1, to be positive. In all our regressions, we cluster standard errors at the city-country level.

3.3 Endogeneity and IV Approach

Our goal is to identify the effect of air connectivity on the spending of Chinese consumers in foreign countries. However, the OLS estimator, γ_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

[16] Using Monte Carlo simulations, Bellemare and Wichman (2022) show that the estimated coefficient becomes more stable as the sizes of dependent and independent variables get larger. Although the size of our explanatory variable, the weekly frequency of direct flights, might be small, their simulation results also indicate that any bias in the estimated coefficient is negligible and does not significantly affect our findings.

transactions even without an air connection. This raises a reverse causality concern—a larger value of transactions might improve flight connectivity, instead of better flight connectivity increasing the value of transactions.

3.3.1 Designing an Instrumental Variable

We introduce a unique instrumental variable (IV) to overcome this endogeneity concern. Our instrument exploits plausibly exogenous variation in air connectivity 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 international flights (excluding China) for which country j is the origin ($\lambda_{jt} = \frac{flight_{jt}}{\sum_j flight_{jt}}$), and $\ln dist_{ij}$ is the natural logarithm of the geographical distance between Chinese city i and country j.[17] The numerator of λ_{jt} is the total number of direct flights departing from country j in year t, and the denominator is the total number of international flights departing from all countries around the world in year t. We exclude flights to China both in the nominator and denominator.

The role of two variables in our IV is similar to the shift-share IV developed by Autor et al. (2013). The authors instrument for the change in US imports from China using other countries' imports from China (i.e., the shock in China's comparative advantage in productivity) and employment shares in regions. These employment shares allow the authors to allocate the impact of the shock to each regions. In contrast to Autor et al. (2013), we instrument for Chinese air connectivity using other countries' air connectivity (i.e., the shock in the comparative advantage in air transportation technology in a foreign country) and trade costs (i.e., the distance between a foreign country and a Chinese city).[18] Airline companies face higher trade costs between more distant markets, and therefore the impact of the air transportation development in destination countries can be attenuated with the distance.[19]

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

[18] Note that our instrument differs from a shift-share instrument because the distance is not a share.

[19] In airline markets in particular, regulations stipulate how long pilots can work on flights, which increases

Our instrument is expected to be negatively correlated with the frequency of direct flights, $\tilde{D}_{ijt}$: a country with a comparative advantage in air transportation is more likely to have direct flights, while city-country pairs that are further apart likely have fewer direct flights connecting them. The negative relationship between distance and air connectivity reflects the fact that there are fewer flights connecting more distant markets, in general (Cristea 2019). We assume that distance affects our dependent variable (value of card transactions) only through air connectivity (our endogenous variable) conditional on the origin-destination FEs.[20] 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.

3.3.2 Identification Assumption

Our key identifying assumption is that the share of the flights departing from country j, λ_{jt}, is uncorrelated with demand shocks in a particular Chinese city for travel to that country in year t. We argue that the relevant exclusion restriction holds because foreign governments—not Chinese city governments—develop destination countries' levels of air connectivity. As such, the degree of a foreign country's air connectivity is plausibly exogenous with respect to 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).[21] The country opened the world's largest airline terminal in Dubai in 2008. Since then, its share of global international direct flights (i.e., the first term in our instrumental variable) has increased substantially. The number of flights arriving in the UAE increased by 52.7% between 2011 and 2016 (Appendix A.3). This and similar government efforts to attract direct flights depend on investment decisions by local governments, not shocks to travel demand in particular

the costs of long-distance air connections (Campante and Yanagizawa-Drott 2017).

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

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

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

Table 2 shows ten countries where the share of the flights coming to a country j, λ_{jt}, increased more than other countries between 2011 and 2016. We also provide the share of flights arriving from China in 2011 and 2016 for those countries in the table. Notably, the share of flights arriving from China has not increased significantly despite their airport expansions in almost all the countries. This indicates that the goal of expanding airports was to attract travelers from all over the world, rather than specifically targeting Chinese travelers. These variations in air transportation development are plausibly exogenous to demand shocks from Chinese cities and thus serve as valid instruments for our analysis.

3.4 2SLS Specification

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

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

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

where we define Z_{ijt} in equation (6). Our first stage coefficient, α_1, captures the relationship between the share of global flights departing from foreign country j, as well as the distance between j and Chinese city i (together making up our IV, Z), and the degree of air connectivity between city i and country j, $\tilde{D}$. In these terms, the exclusion restriction we describe above holds if our IV—Z—is uncorrelated with other unobserved determinants of card transaction values between i and j, ϵ. Our second stage coefficient of interest, γ_1, delivers the causal impact of air connectivity on card transactions made by consumers from city i in destination country j.

4 Results

We estimate the impact of air connectivity on 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 3.4, 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.

4.1 Main Results

In our main specification, we analyze the impact of the improvement in the weekly frequency of direct flights on card transaction values. Column 2 of Table 3 shows the regression result with the inclusion of three types of fixed effects (FEs): origin-specific time-varying FEs, destination-specific time-varying FEs, and city-country pair FEs. The IV coefficient on the frequency of direct flights is positive and significant. Specifically, a 1% increase in the weekly frequency of direct flights leads to a 1.82% increase in cross-border travel spending. The average weekly frequency of direct flights across destination countries is 3.75 over the data period.[22] Intuitively, our regression suggests that in a city with the average weekly frequency, if an airline offers one additional weekly direct flight, the travelers in that city spend 48.53% more in that destination country. We report first-stage results at the bottom of the table. The coefficient on the IV is negative and highly significant. More importantly, the first-stage F statistic is 24.57, which suggests that we can reject the null of a weak instrument.[23]

The IV coefficient is larger than the OLS coefficient reported in column 1. This downward bias does not preclude potential reverse causality, but it does suggest there is a stronger negative force diminishing the relationship between air connectivity and the value of card transactions. The difference between our 2SLS and OLS coefficients underscores the distinction between the "treatment" in our OLS and 2SLS specifications, and their effects on

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

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

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).

In columns 3 and 4, we limit and expand our sample size to check if the results differ substantially based on our sample selection. One potential issue is that most Chinese international travelers are from Shanghai and Beijing, and therefore our estimate may be largely driven by the travelers from these two cities.[24] We drop the city-country pairs that include Shanghai or Beijing and re-estimate our 2SLS specifications to see whether our findings hold in this restricted sample. Column 3 of Table 3 shows that the 2SLS coefficients with the restricted sample are very similar to the ones with the full sample (shown in columns 2 of Table 3) in terms of size, significance, and sign. These results suggest that our estimates are not specific to the two largest Chinese cities.

We also examine how our results change when we expand the scope of Chinese cities in our sample. We have so far focused on cities that had airports during our sample period and analyzed the effect of the number of weekly direct flights on overseas travel spending. Here, we include the additional group of Chinese cities—cities that do not have airports. If we include those cities in our sample, we expect that the size of the coefficient of interest will be larger than our main result because our baseline group would be cities without access to air transportation, instead of cities without access to international flights. Our results after including cities without airports appear in column 4 of Table 3. The coefficient of the 2SLS

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

estimate is positive and significant, and as expected, the size is larger than the coefficient in our main result (shown in column 2 of Table 3) because it includes the variation of air connectivity due to an establishment of airports.

4.2 Robustness Checks

Our IV regressions show that an increase in the number of weekly direct flights from a city to a country positively affects the value of card transactions between that city-country pair. We test whether our main results (column 2 of Table 3) are robust using alternative measures of air connectivity and travel spending.[25] We also consider an alternative identification approach for causal inference.

4.2.1 Alternative Specifications with Weekly Frequency of Direct Flights

One of the robustness checks is to employ alternative specifications of our dependent variable. First, we replace the value of card transactions with the number of card transactions. In our descriptive analysis (Section 2.3), we observe a positive correlation between the number of transactions and the weekly frequency of direct flights. Column 1 of Table 4 reports the regression result. We find that a 1% increase in weekly direct flights leads to a 0.30% increase in the number of card transactions. The positive and statistically significant result is similar to the main result using the value of transactions.

In addition, we take into account that Chinese travelers possibly visit other countries close to their first arrival countries. This concern is especially relevant to travel in European countries, where multiple destinations can be easily accessible. To address this issue, we group European countries into four geographical regions and measure the frequency of direct

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

flights for each European region.[26] Column 2 of Table 4 shows the result of this alternative regression, and the coefficient closely aligns with our main regression result.

We also consider a scenario where Chinese travelers have the option to use airports located in neighboring cities. We assume that travelers are willing to drive up to 200 km to access other airports, meaning we consider all flights departing from airports within a 200 km radius of the central location.[27] In other regressions, Chinese travelers access only the international direct flights departing from their residing cities. In this alternative specification, travelers can benefit from flights departing from nearby cities. Since travelers are endowed with a larger set of international flights, the impact of a new international flight route becomes less influential. The regression result supports this assumption, as we observe a smaller coefficient on the weekly frequency of direct flights (column 3 of Table 4).

4.2.2 Travel Time

We consider travel time from Chinese cities to foreign countries as an alternative measure of air connectivity. While we considered only international direct flights in the main specification, we now include indirect flight connections to travel to destination countries. To measure travel time, we first construct all possible flight routes with up to two stops at domestic airports and one stop at a foreign airport. We add a three-hour layover time for every stop to the total flight duration. We then select the route with the shortest travel time among all possible flight routes.[28] Additional procedures to measure travel time are outlined in Appendix Section B. The unit of travel time is an hour.

The result of the IV regression is presented in column 2 of Table 5. The coefficient of travel time is 3.64 and significant at the 1% level, which indicates that a 1% decrease in travel time leads to a 3.63% increase in the value of transactions. The average travel time is 13.39 hours in our data. This regression result suggests that if travelers in a city with average travel time can reach a foreign country an hour faster than before, the transaction value will increase by 28% in this city-country pair. We observe a similar statistically significant

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

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

[28] We cannot construct any flight routes to some foreign countries from 45 cities (out of 192 cities), even with three stops. Therefore, the number of observations is smaller than in the main specification.

coefficient even when excluding Beijing and Shanghai from our sample (column 3 of Table 5).

Opening a new direct flight route not only shortens the travel time to the country connected directly by the flight but also indirectly reduces the travel time to the third country. For example, there was no direct flight from Chongqing to the UK between 2011 and 2015, and travelers from Chongqing flew to Beijing and then took a flight to the UK in 2011. However, in 2012, a new direct flight to Finland opened, which enabled travelers to reach the UK through Finland. The direct flights to Finland reduced travel time to the UK by an hour. Finally, in 2016, another new direct flight to the UK opened, that allowed travelers to visit the UK four hours faster without any connections. In our data, a new direct flight route reduces travel time by 1.77 hours on average.[29] Our baseline result (in column 2 of Table 3) suggests that one additional weekly frequency of direct flight increases the transaction value by 48.53%. A new opening air route increases at least one weekly frequency, which can increase transaction value by 49.56% ($28 \times 1.77 = 49.56\%$). This indicates that both measures of air connectivity (i.e., weekly frequency of direct flight and travel time) have a similar impact.

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

5 Further Analyses

We showed that the development of air transportation networks leads to an increase in trade in travel services using cross-border card transaction data. In this section, we further investigate our findings with the card transaction data by comparing them to the effect on

[29] A new flight route reduces travel time by 3.31 hours by providing a non-stop flight to a destination, while a traveler can save one hour by using the new non-stop destination as a transit airport.

trade in goods. This allows us to study how shocks to consumer tastes and preferences toward destination countries affect trade in travel services.

5.1 Trade in Goods

Improvement in air transportation networks affects not only consumer travel but also trade in goods. One may assume that an increase in travel services would have a positive spillover effect on trade in goods, particularly in the context of consumer goods. Travelers experience new products in countries they visit and may start purchasing the products after their travels. Thus, more direct flight connections increase the number of travelers (i.e., increase imports of travel services), which in turn leads to an increase in imports of goods from the countries with more frequent flight connections.[30] 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.[31] An increase in the weekly frequency of direct flights can affect trade in goods directly (by increasing freight capacity) and indirectly (by providing travelers with more exposure to foreign products).

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

We begin our analysis by examining the impact of air connectivity on the value of total imports, but the coefficient does not show statistical significance (column 1 of Table 6). Therefore, we further explore the effect on the imports of consumer products, which are more relevant to consumption by travelers, in various industries. Specifically, we refer to UNCTAD's categorization for consumer products and run regressions using the value of imported consumer products in each industry at the one-digit level of the SITC Revision 4.

While the coefficient on the regression with total consumer goods imports is not sta-

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

[31] 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).

tistically significant (column 2 of Table 6), the results exhibit heterogeneity across different industries, as illustrated in Figure 6. Interestingly, we observe that the imports of food/beverage and pharmaceutical/cosmetic products increase by around 1% with a 1% increase in the weekly frequency of direct flights.[32] It is worth noting that these products are mostly transported by air. For instance, food/beverage are perishable and time-sensitive products (Djankov et al. 2010). Similarly, pharmaceuticals have higher unit values compared to other products and are primarily shipped using a fast and expensive mode of transportation (Harrigan 2010).[33]

5.2 Effects of Political Conflicts

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

During the data period, there are four notable conflicts between China and Japan, the Philippines, South Korea, and Norway.[34] 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

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

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

[34]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).

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.[35] 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 imports of travel services and goods. First, we create an indicator of boycotts, $\mathcal{I}[Boycott_t]$, that takes one for a country under the conflict in the year of each event. Specifically, the indicator equals one for Japan in 2012, one for the Philippines in 2012, one for South Korea in 2016, and one for Norway in 2011.[36] Second, we add the interaction term between the weekly frequency of direct flights ($\tilde{D}_{ijt}$ in equations 7 and 8) and $\mathcal{I}[Boycott_t]$ to the 2SLS specification introduced in Section 3.4.

The results are presented in Table 7. We find a negative and significant coefficient on the interaction term between air connectivity and boycott (column 1). This result indicates that the effect of air connectivity on travel service trade decreases when there is a political conflict between China and a destination country. Interestingly, the coefficient on the interaction term is not statistically significant concerning the imports of consumer goods (columns 2). We continue to see statistically insignificant results when considering only imported consumer goods in the food/beverages and pharmaceuticals/cosmetics industries. These industries experience an increase in the value of imports due to the development of air connectivity. Overall, our findings suggest that a rise in political conflicts—an adverse shock of consumer preferences towards destination countries—can offset the promoting effect of air connectivity on cross-border travel but not on trade in goods.

[35]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.

[36]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.

6 Conclusion

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

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

This study provides insight into the relationship between investment in air connectivity—via improvements in airports, for example—and trade in services and goods, which could inform policies meant to promote economic relationships with foreign countries. To precisely gauge the effect of investment in air connectivity on cross-border travel, policymakers need to be aware of the mediating role of local consumer preferences (such as cultural ties and sentiments towards destinations). Our results suggest that encouraging cultural exchanges with and creating welcoming sentiments towards foreign countries are useful to boost the impact of air connectivity on cross-border travel.

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Figures

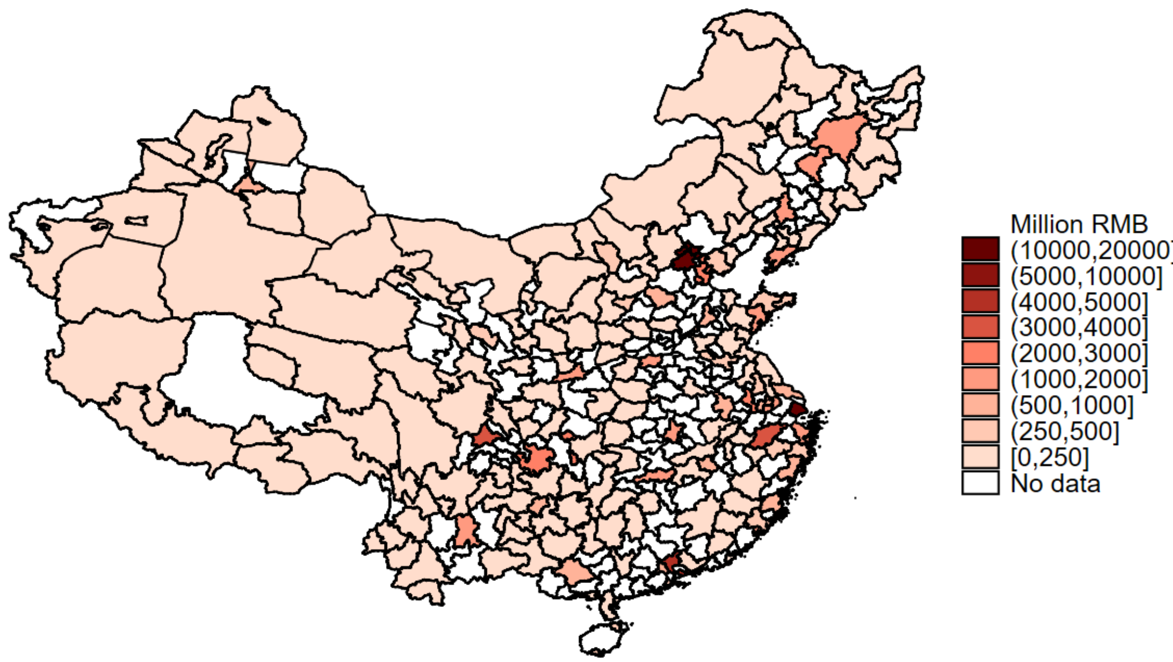


Figure 1: Change in Card Transaction Values from 2011 to 2016 in Mainland Chinese Cities

Notes: The value of transactions is in millions RMB. The map shows the change in the total value of transactions between 2011 and 2016 in the cities in mainland China. All transactions are made by Chinese residents.

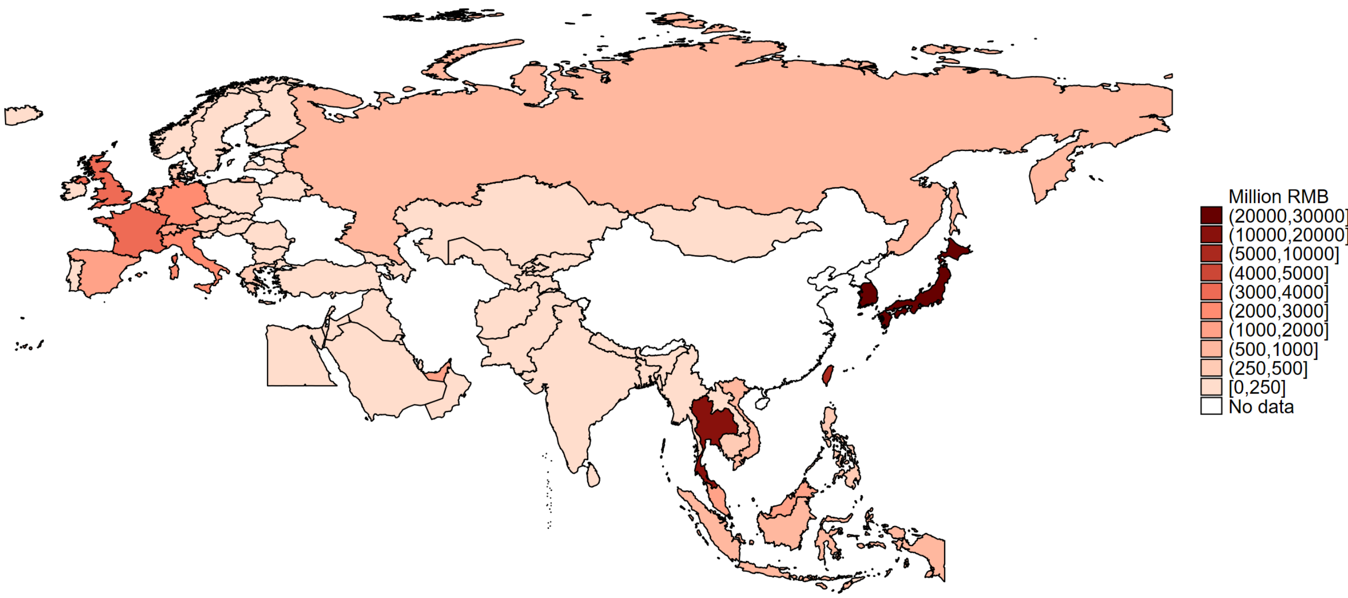


Figure 2: Change in Card Transaction Values from 2011 to 2016 in Destination Countries

Notes: The value of transactions is in millions RMB. The map shows the change in the total value of transactions in each country in our sample. All transactions are made by Chinese residents.

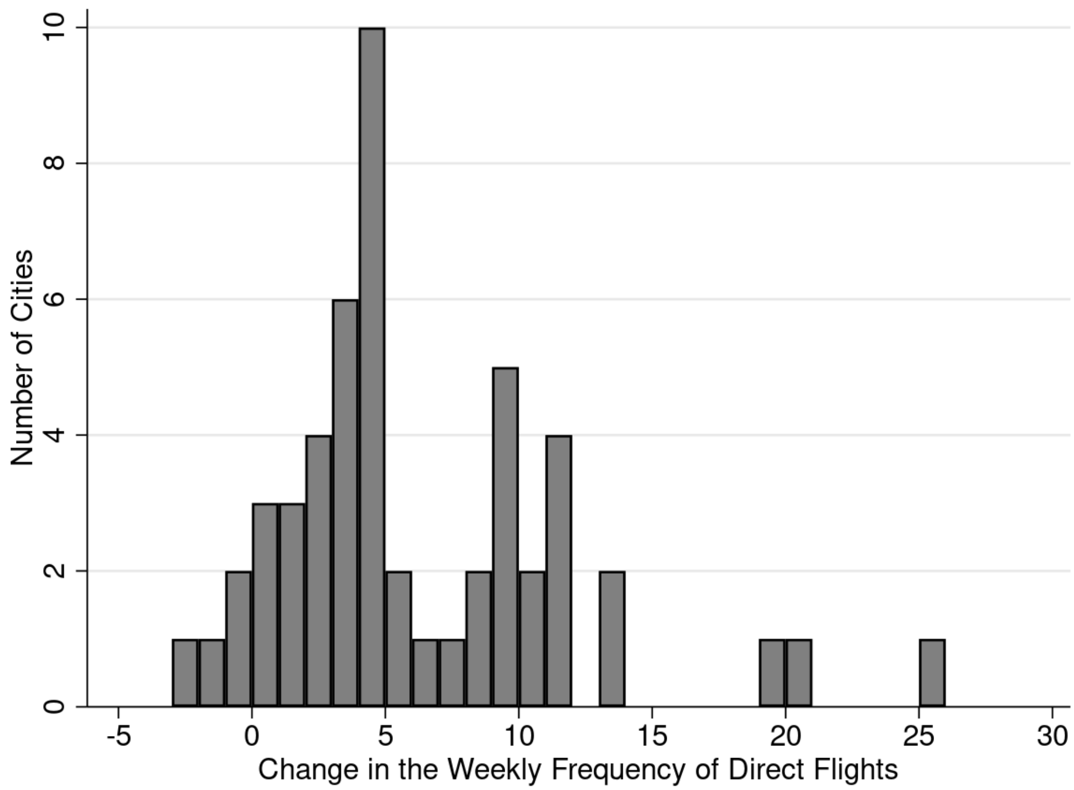


Figure 3: The number of Chinese cities with a change in air connectivity from 2011 to 2016

Notes: The figure shows the distribution of the number of Chinese cities with the change in the average weekly frequency of direct flights between 2011 and 2016. Each bar represents the number of Chinese cities, and the size of the bin is one weekly frequency. We focus on the cities with at least one international direct flight in 2011. Before considering the difference from 2011 to 2016, we calculate the average number of direct flights per week across destination countries.

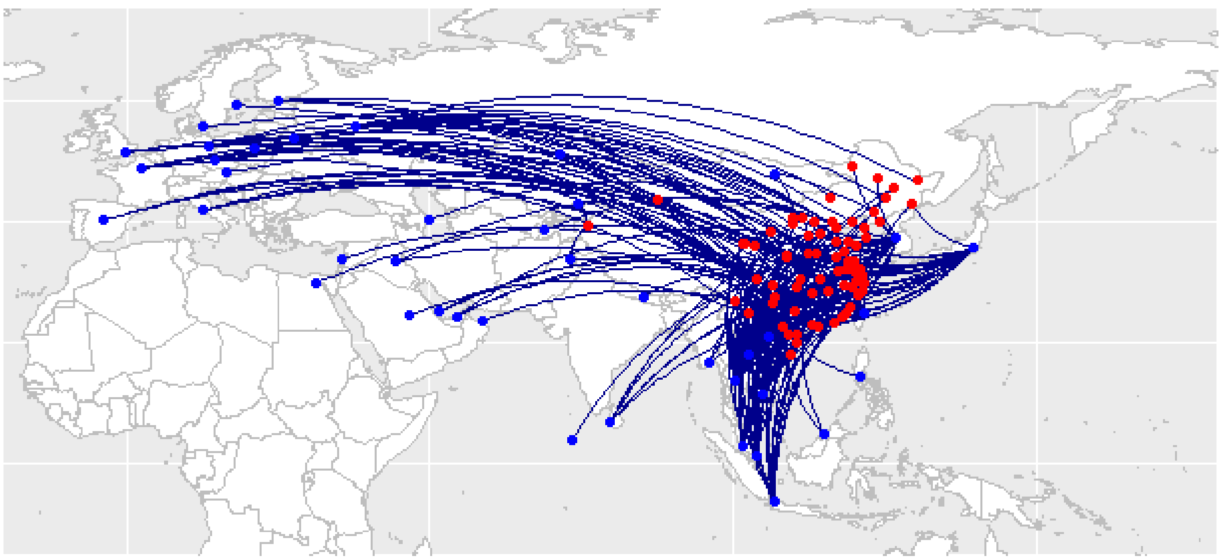
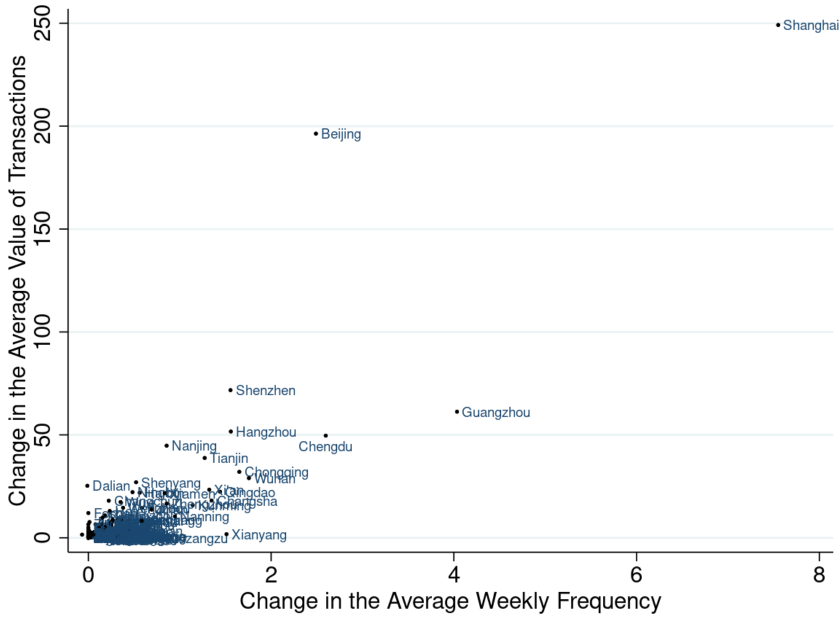
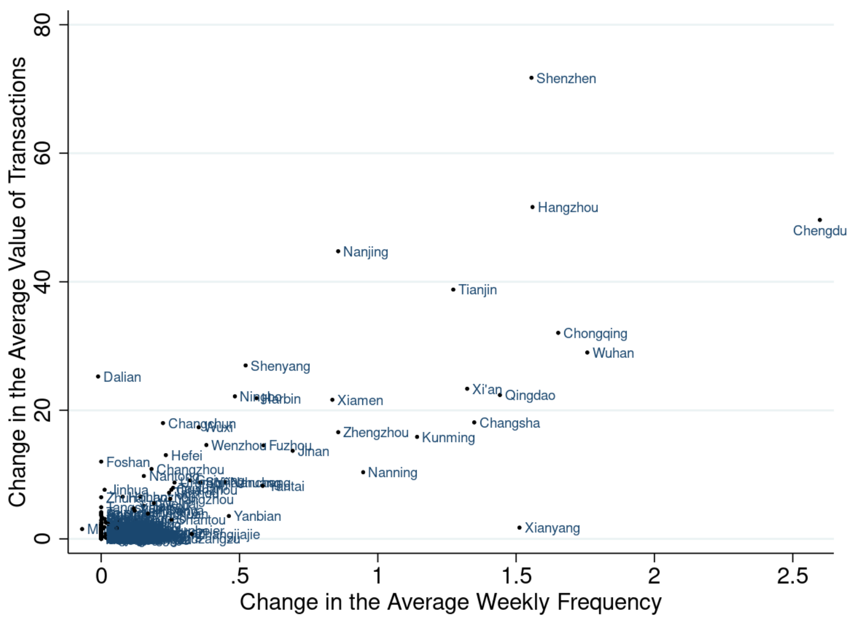


Figure 4: New Direct Flight Routes in 2016

Notes: The purple lines show the new direct flight routes from Chinese cities (with red dots) to the destination countries (with blue dots) in 2016 compared to 2011. We use the air routes in our data sample.



(a)



(b)

Figure 5: Change in air connectivity and the value of transactions

Notes: Panel (a) and Panel (b) show the correlation between the change in the value of transactions between 2011 and 2016 (on the y-axis) and the change in the weekly frequency of direct flights from 2011 to 2016 (on the x-axis). The data for these figures are at the Chinese-city level. We calculate the average of the value of transactions and frequency of direct flights across destination countries. We excluded Shanghai, Beijing, and Guangzhou to focus on other Chinese cities in Panel (b).

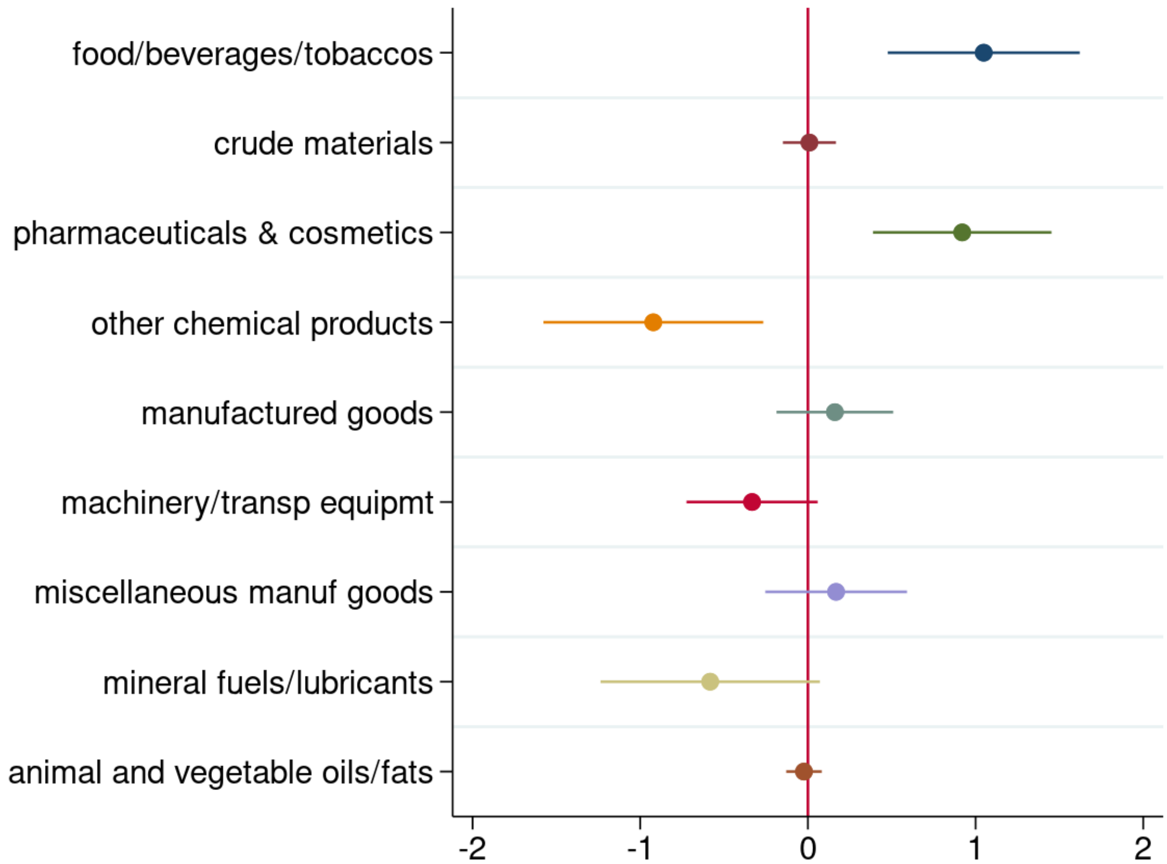


Figure 6: Estimates on Consumer Goods Imports by Industries

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

Tables

Table 1: Summary Statistics

Variables	Mean	P(50)	Min	Max	SD	Observations
Main Data						
Card transactions						
Value (millions RMB)	9.34	0.035	0	9,626.68	99.62	58,860
Number of transactions	5,253.09	16.00	0	5,399,033	78,575.16	58,860
Flight schedules						
Weekly frequency of direct flights	0.45	0	0	473.56	5.72	58,860
Travel time (hours)	13.39	14.12	0.83	25.22	4.58	46,260
Imports						
Value (millions RMB)	92.37	0.001	0	42071.6	887.61	58,860

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

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

Country	Share 2011	Share 2016	$\hat{\lambda}$
United Arab Emirates	0.0159	0.0143	0.0064
Turkey	0.0060	0.0047	0.0057
Saudi Arabia	0.0016	0.0021	0.0048
Japan	0.2131	0.2285	0.0036
Qatar	0.0141	0.0144	0.0031
South Korea	0.2873	0.3153	0.0030
Taiwan	0.2368	0.2465	0.0024
Thailand	0.0861	0.2618	0.0022
Vietnam	0.1042	0.1372	0.0017
India	0.0134	0.0129	0.0013

Note: This table lists the share of flights from China to the countries with the largest change in the share of total international flights departing from country j (the part of our IV, λ_{jt}).

Table 3: Main Results

	Value of transactions			
	Baseline sample		Excl. big cities	Cities w/o airports
	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Weekly Frequency	0.075***	1.823***	1.874***	3.763***
	(0.022)	(0.436)	(0.437)	(1.008)
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	58,860	58,860	58,020	100,296
First Stage				
IV		−39.383***	−40.215***	−22.386***
		(7.951)	(7.997)	(5.621)
KP Wald rk F-statistic		24.532	25.290	15.862
KP LM statistic		24.786	25.578	16.052
KP LM p-value		0.000	0.000	0.000
AR Wald test p-value		0.000	0.000	0.000

Notes: Columns 1 and 2 show the baseline results. In column 3, we drop the city-country pairs that include Shanghai or Beijing. In column 4, we include cities without airports. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

Table 4: Robustness Checks 1

	Number	Value of transactions	
		European regions	Nearby airports
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Weekly Frequency	0.302***	1.732***	1.577***
	(0.077)	(0.397)	(0.316)
Origin city-year FEs	Yes	Yes	Yes
Foreign country-year FEs	Yes	Yes	Yes
Origin city-foreign country FEs	Yes	Yes	Yes
Observations	58,860	58,860	100,296
First Stage			
IV	−39.383***	−41.450***	−53.408***
	(7.951)	(7.921)	(10.227)
KP Wald rk F-statistic	24.532	27.383	27.270
KP LM statistic	24.786	27.509	27.715
KP LM p-value	0.000	0.000	0.004
AR Wald test p-value	0.000	0.000	0.000

Notes: The regression in column 1 uses the number of transactions as a dependent variable instead of the value of transactions. In column 2, we group European countries into four regions (Central and Eastern Europe, Northern Europe, Southern Europe, and Western Europe) and measure the frequency of direct flights for each European region. In column 3, we consider all airports located within 200 km of each Chinese city. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

Table 5: Robustness Checks 2

	Value of transactions		
	All cities		Excl. big cities
	OLS	2SLS	2SLS
	(1)	(2)	(3)
Travel Time	−0.157***	−3.636***	−3.809***
	(0.024)	(1.349)	(1.384)
Origin city-year FEs	Yes	Yes	Yes
Foreign country-year FEs	Yes	Yes	Yes
Origin city-foreign country FEs	Yes	Yes	Yes
Observations	46,260	46,260	45,420
First Stage			
IV		16.174***	16.518***
		(5.623)	(5.680)
KP Wald rk F-statistic		8.275	8.457
KP LM statistic		8.310	8.488
KP LM p-value		0.004	0.004
AR Wald test p-value		0.000	0.000

Notes: We replace weekly frequency with the log of travel time as our independent variable. We assume that 1 layover takes 3 hours. Columns 1 and 2 show the main results of travel time. In column 3, we drop the city-country pairs that include Shanghai or Beijing. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. KP: Kleibergen-Paap, AR: Anderson-Rubin.

Table 6: Effect of Air Connectivity on Goods Imports

	Value of import		
	Full Sample	Consumer goods	Non-consumer goods
	(1)	(2)	(3)
Weekly Frequency	−0.246	0.130	−0.256
	(0.462)	(0.337)	(0.456)
Origin city-year FEs	Yes	Yes	Yes
Foreign country-year FEs	Yes	Yes	Yes
Origin city-foreign country FEs	Yes	Yes	Yes
Observations	58,860	58,860	58,860

Notes: This table presents the results of IV regressions with the value of imports. We do not report the first stage regression result as they are the same as that in Table 3. The categorization for consumer goods is from the UNCTAD and was obtained from the World Integrated Trade Solution (WITS) website. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Boycott and Cultural Shock

	Values			
	Card transactions (1)	Consumer goods (2)	Food (3)	Pharma+Cosmetics (4)
Weekly Frequency	1.980***	0.130	1.081***	0.388**
	(0.486)	(0.360)	(0.317)	(0.190)
Weekly Frequency × Boycott	−0.208***	0.000	−0.042	0.034
	(0.053)	(0.038)	(0.035)	(0.028)
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	58,860	58,860	58,860	58,860

Notes: This table presents the results of IV regressions examining the impact of political conflicts on the effects of air connectivity on bilateral trade. We use the value of card transactions as the dependent variable in column 1, and the value of consumer goods imports in column 2. In column 3, we specifically focus on consumer goods in the food, beverages, and tobacco industries, while in column 4, we analyze the pharmaceutical and cosmetics industries. The political conflicts affecting Chinese consumers include the boycott of South Korea in 2016, the boycott of Japan in 2012, the boycott of the Philippines in 2012, and the boycott of Norway in 2011. The F statistics in the first stage regression is 22.02. Standard errors, clustered at the city-country level, are in parentheses. Significance levels are $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Appendix A Appendix

A.1 Destination Countries

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

Table A.1: 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	Tajikistan	Taiwan
Thailand	Timor-leste	Turkey	United Arab Emirates
United Kingdom	Uzbekistan	Vietnam	

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

A.2 City-Country Pairs with Largest Value of 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 Air Connectivity in 2011 and 2016

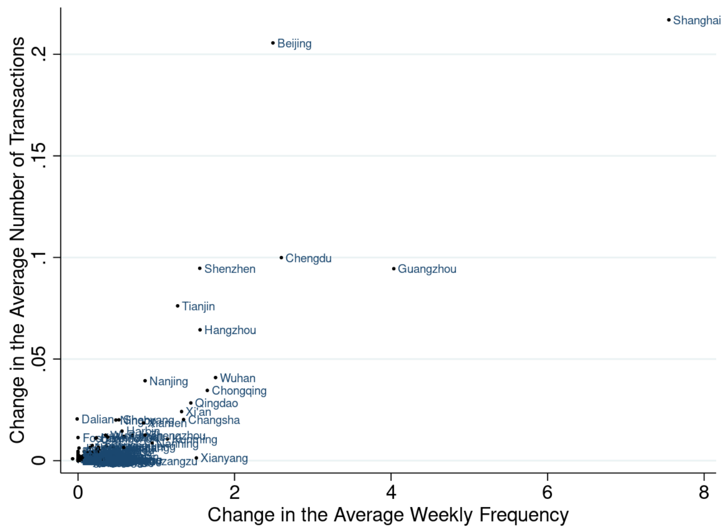
One of the components of our IV is the share of the number of flights departing a foreign country to total direct flights across the world. In Table A.3, we list the countries with the number of total outbound flights in 2011 and 2016. The countries with larger changes in that number contribute to variations in our IV.

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

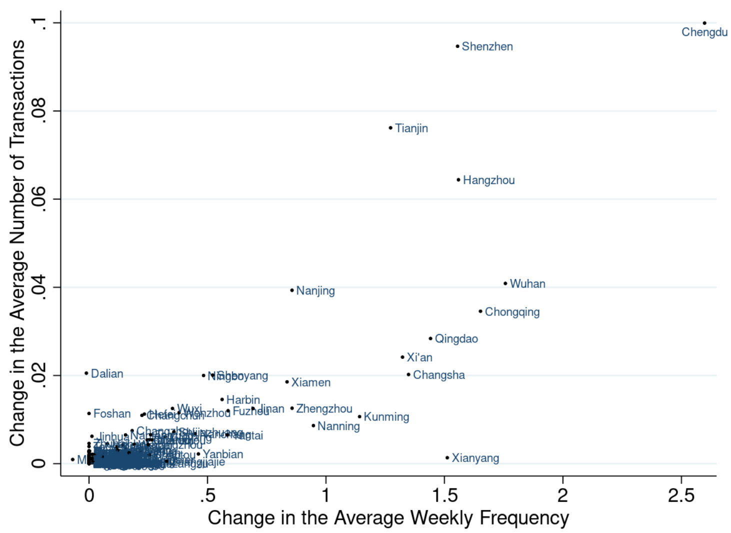
Country	2011	2016	Change	Percentage Change
United Arab Emirates	204,239	311,963	107,724	52.7%
United Kingdom	652,308	757,293	104,985	16.1%
Turkey	152,501	242,752	90,251	59.2%
Spain	411,373	484,070	72,697	17.7%
Saudi Arabia	81,558	148,373	66,815	81.9%
Japan	121,180	183,392	62,212	51.3%
South Korea	86,861	135,877	49,016	56.4%
Qatar	65,012	110,774	45,762	70.4%
Thailand	105,348	149,051	43,703	41.5%
Taiwan	66,535	105,451	38,916	58.5%
India	124,020	161,777	37,757	30.4%
Italy	353,339	390,640	37,301	10.6%
Netherlands	210,521	247,306	36,785	17.5%
Greece	77,035	108,384	31,349	40.7%
Malaysia	101,772	132,454	30,682	30.1%
Poland	87,968	118,135	30,167	34.3%
Germany	649,054	678,885	29,831	4.6%
Portugal	99,329	126,971	27,642	27.8%
Ireland	92,931	119,556	26,625	28.7%
France	457,523	483,516	25,993	5.7%

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

A.4 The Number of Transactions with Air Connectivity



(a)



(b)

Figure A.1: Air Connectivity and the City-Level Card Transaction Numbers

Notes: Panel (a) and Panel (b) show the correlation between the change in the number of transactions between 2011 and 2016 (on the y-axis) and the change in the weekly frequency of direct flights from 2011 to 2016 (on the x-axis). The data for these figures are at the Chinese city level. We calculate the average of the number of transactions and frequency of direct flights across destination countries. We excluded Shanghai, Beijing, and Guangzhou to focus on other Chinese cities in Panel (b).

Appendix B Data Appendix: OAG Analyzer

- Weekly frequency of direct flights
  - The data is at the air-carrier level. We use only the flights run by operating carriers and exclude code-share flights.
  - We consider all flights arriving in destination countries, regardless of the cities of arriving airports.
  - We add names of the cities with airports to the original data using the table provided by OAG. We also searched on the internet to identify airports serving two cities. The following airports serve two cities: Yangzhou Taizhou International Airport (serving Taizhou and Yangzhou), Xining Caojiabao International Airport (serving Haidong and Xining), Xi'an Xianyang International Airport (serving Xianyang and Xi'an), and Lhasa Kongga International Airport (serving Shannan and Lhasa).
  - OAG records flights with stopovers, not just direct flights. For flights with stopovers at domestic airports before departing for foreign countries, we keep only the flights bound for foreign countries. For example, a flight route from Chongqing to Japan connects through Shanghai. We focus on direct flights connecting a Chinese city with a foreign country (e.g., flights from Shanghai to Japan) and exclude domestic stopover flights (e.g., flights from Chongqing to Japan).
  - Regarding flights with stopovers at international airports, we use only the flights directly connecting Chinese cities with foreign countries. For example, there is a stopover flight departing from Guangzhou to Sri Lanka via Thailand. We keep only the flight from Guangzhou to Thailand.
- Travel time (for Section 4.2.2)
  - We identify the most frequent flight routes to destination countries. For example, flights from Beijing to Japan arrive at different airports such as Narita, Haneda, Osaka, New Chitose (located in Hokkaido), and Naha (located in Okinawa). We

use the travel time of the flight between Beijing and Narita because flights to Narita are the most frequent from Beijing.

- There are some extremely short elapsed times in the data. We exclude the route if the data suggest that a plane travels at speeds exceeding 1,000 km/hour.
- Even on the same flight route, the elapsed time can vary slightly in different flight schedules. We calculate the average flight time using the frequency of flights as weight in each flight schedule. This allows us to have the same elapsed time on the same flight routes over the data period.
- After cleaning the data, we consider all possible flight routes with up to three stops (two stops at domestic airports and one stop at a foreign airport). We add a three-hour layover time for every stop to the total elapsed time. We then select the route with the shortest travel time among all of the possible flight routes.
- We keep city-country pairs with travel time recorded over our data period.