Prepared for the 2019 ASSA-AREUEA Conference

International Travel Costs and Local Housing Markets

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Abstract: This paper identifies the effect of international travel costs on local housing markets. The international travel cost is measured by whether an American city has launched a nonstop flight to a Chinese city. Using differences-in-differences models, we find that after an American airport connected with China via a nonstop flight, the monthly number of Chinese homebuyers in a county nearby the airport increased by about 0.4 (the mean is 0.9); local housing prices at the county level on average increased by $5900 (4%). We also find a significant decrease in the number of local non-Chinese homebuyers, suggesting a displacement effect in the local housing markets by out-of-town homebuyers. Our findings imply that the spatial equilibrium model based on inter-city migration within a country can be largely generalized to international migration. Our study also contributes to the literature on the economics of air travel and out-of-town homebuyers.

Keywords: Nonstop flight; international travel; housing markets; out-of-town homebuyers; difference-in-difference model

JEL Code: F22, F60, J60, R10, R23, R30, R40

1 Introduction

The cost of transporting people, goods, and information is the fundamental determinant of the spatial distribution of population, production, and other economic activities. In the classical monocentric city model, commute cost determines the land rent profile over space within a city (Brueckner, 1987). The evolution of transport technology shapes the dynamic patterns of residential and employment location over space within a city (LeRoy and Sonstelie, 1981). With free migration across cities, transport cost serves as a centrifugal force to determine the sizes of cities and local labor markets in a system of cities within a country, to achieve a spatial equilibrium (Fujita and Thisse, 2002; Redding and Turner, 2015). However, the role of transport cost across international cities is less explored in the urban economics literature.

This paper makes a contribution by identifying the effect of international travel costs on local housing markets. The international travel cost is measured by whether an American city has launched a nonstop flight to a Chinese city. A nonstop flight connecting an American city and China is expected to reduce travel costs between these two countries. Presumably, more Chinese people will then travel to the US as visitors, immigrants, investors, or even commuters. Using the CoreLogic housing transaction data and a differences-in-differences approach based on the variations in the timing of launching nonstop flights in different American cities, we find that after an American city connected with China via a nonstop flight, the monthly number of Chinese homebuyers in a county nearby the airport increased by 0.44 (the mean is 0.88); local housing prices at the county level on average increased by $5,865, or by 3.7%. We also find a significant decrease in the number of local non-Chinese homebuyers, suggesting a displacement effect in the local housing market by out-of-town homebuyers.

Our study complements two strands of emerging literature. The first strand identifies the economic and social impacts of reduced domestic or international air travel costs. Brueckner (2003) finds that airline traffic (total passenger enplanement) in US cities promotes urban employment, with an elasticity of 0.1, but only for service industries, not for manufacturing industries, suggesting that air travel promotes long-distance face-to-face communications. Similarly, Blonigen and Cristea (2015) find that airline traffic promotes growth in population, income, employment: for example, a 50% increase in a city's air traffic growth rate generates 2~4% increase in annual population growth rate. Catalini *et al.* (2016) provide more direct evidence that the entry of Southwest Airlines into US cities from 1993 to 2010 reduces air fares by 20% and causes scientific collaborations to increase on average by 50%, specifically, 36% in chemistry, 26% in physics, 49% in engineering, and 85% in biology during 1991-2012.

A few studies estimate the economic impact of international air travel costs. Bel and Fageda (2008) find that availability of direct, intercontinental flights in Europe significantly affects large firms' headquarters location. Yilmazkuday and Yilmazkuday (2014) estimate that one direct flight reduces trade costs between two (international) cities by about 305 miles in distance-equivalent terms and having more direct flights reduces trade costs further. Campante and Yanagizawa-Drott (2016) find that connecting with other international cities via international flights generates local economic growth (measured by night light coverage) and facilitates capital flowing from high- to low-income countries. Since capital flow does not directly depend on air travel, they infer that reducing international travel costs promotes face-to-face communications across countries. Their identification uses a regression discontinuity design method based on the technological fact that cities with distance above 6,000 miles are not connected via international flights until two long-range airplane models are invented (Boeing 747-400 in 1989 and Airbus A330 and A340 in 1993-94). Our study differs from these in that we focus on a different consequence of direct, international flights—their effects on local housing markets.

The second strand of literature studies the economic impact of out-of-town homebuyers. Large cities in the world generally attract real estate buyers from outside, which raises much concern from local residents and governments when the number of out-of-town real estate buyers reach a certain threshold.[1] Sá (2016) finds that out-of-town buyers (foreign companies) increase housing prices in England and Wales. Chinco and Mayer (2016) identify that out-of-town homebuyers in US cities behaved like misinformed speculators. Cvijanovic and Spaenjers (2017) find that out-of-town (foreign) buyers displace local residents in high-quality neighborhoods of Paris. Favilukis and Nieuwerburgh (2017) construct a structural model and show that an inflow of out-of-town homebuyers pushes up local real estate prices, rents, and wages and in general slightly reduces local city welfare. Instead of looking at the impact of out-of-town homebuyers, we focus on one of the causes that foreigners become out-of-town homebuyers—a decrease in international travel costs.

While in this study we are unable to directly test whether the decrease in international travel costs causes more immigrants from China to the US, our

[1] Many news articles report stories that Chinese real estate buyers flow into world cities such as Vancouver, New York, Los Angeles, Paris, London. See for example, https://www.nytimes.com/2015/11/29/business/international/chinese-cash-floods-us-real-estate-market.html.

results imply that regardless of additional institutional regulations such as visa policy, compared with inter-city migration within a country, a decrease in international travel costs does facilitate moving people across countries. This suggests that spatial equilibrium models based on inter-city migration within a country can be largely generalized to the inter-country migration.

The rest of the paper is organized as follows: Section 2 introduces the data; Section 3 specifies the econometric models and discusses the causal identification strategies; Section 4 presents the results; and Section 5 concludes.

2 Data

We obtain the schedule information for nonstop flights between US airports and China from the Federal Aviation Administration website. Table 1 lists all the fourteen US airports that have had at least one nonstop flight to China.[2] The earliest date of direct flights from the USA to China is in January 2000 (Detroit, Los Angeles, and San Francisco) and the most recent is in December 2016 (but our housing data are up to only 2014). Since airports generate negative externalities such as noise and pollution, and zoning regulations may also be imposed on the airport areas, we focus on counties that are located within 150 mile radius of airports with nonstop flights to China and call such counties "direct flight areas."[3] These counties serve as our "treatment group" where "treatment" refers to the launching of a nonstop flight to China.

(Insert Table 1 here)

To select a "control group," we first choose the top 60 airports in the US, ranked by the number of passengers boarding in 2015 and 2016.[4] We then exclude those airports with direct flights to China; for the remaining airports without direct flights to China, we select the counties that are located within a 150 mile buffer surrounding an airport as the "control group." If a county is located in a buffer that overlaps both an airport with nonstop flights and an airport without nonstop flights, then we assign this county into "direct flight areas." Figure 1 plots all the counties and the top 60 airports and also demonstrates the buffer areas for airports with and without a direct flight to China.

(Insert Figure 1 here)

[2] Two direct flight airports, HNL at Honolulu, HI and ANC at Anchorage, AK, are not listed here.
[3] We also tried 50 and 200 miles radius as the cutoff and the results are similar.
[4] The passenger boarding numbers are from website https://www.faa.gov.

We focus on three types of major outcome variables: the number of homebuyers from the mainland China (Chinese homebuyers), median housing prices, and the number of local non-Chinese homebuyers in each American county each month. We construct these variables from the CoreLogic's historical real estate transaction data.[5] CoreLogic collects and maintains the most comprehensive property data in the US. We select the housing sales data for the 2000~2014 period. The data includes transaction information such as buyers' names, address of the property, transaction price, transaction date, etc. We use the median of the prices of transactions occurring in a month in a county to measure the overall housing price level in a county in that month. [6] The housing price levels are deflated by consumer price indexes.

To count the number of homebuyers who are Chinese from the mainland China, we use a multi-step name-ethnicity matching algorithm. The spelling of Chinese names, *Pingyin*, is distinctive and can be easily distinguished from any foreign names and Chinese names from Hong Kong, Macao, and Taiwan with Cantonese spelling. We first use the top 300 sir names in China to match the sir names of the home buyers; these top 300 sir names are so commonly used in China that they cover about 98 percent of Chinese population.[7] In the second step, we wrote a program to match name-ethnicity links in the "Ethnea" database, a probabilistic ethnicity predictor database based on bibliographic records.[8] We then drop given names that are not Chinese because these people are most likely Chinese immigrants who have stayed in the US for many years or Chinese from Hong Kong, Macao, or Taiwan. The remaining Chinese names are most likely from the mainland China.

3 Model specification and identification strategy

We first present a set of summary statistics to show the descriptive results. The first panel in Table 2 shows the summary statistics for the full sample, and the second and third panels show the summary statistics for key variables for the counties in the treatment group before and after being "treated." Compared with the time period before the first direct flight to China is launched in a nearby airport, on average the number of Chinese homebuyers increased from 0.9 to 1.7

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[5] For more information about the CoreLogic data, please refer to www.corelogic.com.
[6] Using the mean of transaction prices in a county-month generates similar results.
[7] According to the 6th population census of China, each of the top 100 sur names has at least 2.04 million population in 2010; the top first sur name, "Li", has 95 million population.
[8] This database is created by Professor Vetle I. Torvik at the Graduate School of Library and Information Science, University of Illinois at Urbana-Champaign. The website of Ethnea database is http://abel.ischool.illinois.edu/resources.html.

per month per county after the first direct flight operates; median transaction price increases from $103,979 to $127,539; and the number of non-Chinese buyers decreased by 11 per month per county. [9] However, these facts cannot be interpreted as causal since many unobservable confounding factors may have affected the local housing markets. One example is that the number of non-Chinese homebuyers could have increased in the counties of the control group after direct flights are launched in nearby airports implying a possible common trend in the U.S. housing markets.

(Insert Table 2 here)

3.1 Before-and-after comparison for treatment group

To identify the causal effect of a direct flight on local housing markets, we first use only the treatment group sample and employ a general difference-in-differences (DD) method that compare the outcome variables before and after a nonstop flight is launched within a county (this is also called interrupted time series analysis). Our baseline before-and-after comparison model is specified as follows:

$$Y_{it} = \alpha_i + \beta_1 AfterDF_{it} + \beta_2 \lambda_t + \varepsilon_{it}, \quad (1)$$

where i indicates county and t year-month. Y_{it} refers to one of these six outcome variables: number of Chinese homebuyers, percentage of Chinese homebuyers among all individual buyers; number of non-Chinese homebuyers, number of local Chinese American buyers, and the level and the logarithm of the median housing price in a county i in month t. $AfterDF_{it}$ is a "treatment" or "policy" dummy variable and equals to one for months after a (first) direct flight to China is launched in an airport within whose 150 mile buffer area a county is located. County fixed effect α_i and year-month fixed effect λ_t are included. β_1 and β_2 are the coefficient vectors to be estimated. ε_{it} is the error term and may not be independently and identically distributed. To incorporate the possible serial correlation within a county, standard errors are clustered at the county level.

In estimating Model (1), we select only the treatment group, the counties that are located within a 150 mile buffer area of an airport that has had at least one

[9] These counties also have a higher share of Chinese American population in 2000 and a higher share of Asian American population in both 1990 and 2000 compared with the counties in the control group. The share of Asian and Chinese population in each county are drawn from the census tract level demographic data provided by Geolytics, Inc.

direct flight to China. Since our housing data cover only 2000~2014, we exclude the counties near the airports that launched their first nonstop flight to China in January 2000 since these counties are always "treated". [10] The key identification assumption is that the policy variable "*AfterDF*" is exogenous to local housing markets conditioning on control variables. We believe that the county fixed effects and year-month fixed effects can control well the unobserved time-unvarying county characteristics and unobserved time trends that may confound the policy effect. Furthermore, whether and when a US airport can launch a nonstop flight is determined by the bilateral "Open Skies" agreement (and very often tough negotiations) between the US and Chinese governments (Beane, 2007; Lei *et al*., 2016). In this sense we believe that the exogeneity of the "policy" can be assured conditioning on county and year-month fixed effect. Therefore, the coefficient β_1 in Model (1) can be interpreted as "causal" effect.

Some airports operate more than one route from the USA to China. For example, Chicago airport launched its first nonstop flight to Beijing in April 2001 and the second to Shanghai in November 2004. Since more routes provide more options for international travelers and may further reduce travel fare due to enhanced competition between airline companies, we expect a stronger impact on local housing markets when more nonstop routes are operting. To test this, we replace the *AfterDF* policy dummy variable by the number of nonstop flights existing in a county in each month (*NumberDF*) and estimate the following model:

$$Y_{it} = \alpha_i + \beta_1 NumberDF_{it} + \beta_2 \lambda_t + \varepsilon_{it} \ . \quad (2)$$

This estimates the effect of "treatment intensity" or the marginal effect of adding one more nonstop route to China. In this case we can also include the airports that had their first nonstop flights in January 2000.

3.2 **DID models for number of buyers**

Although we argue that Model (1) estimates a causal effect based on the within-county variation of policy, there still may be omitted confounding factors for the whole treatment group. For example, the counties in the direct flight areas may have common characteristics based on which airline companies make decisions on whether to offer nonstop flight services or not. Some of these special characteristics may not be controlled by location fixed effects and year-month

[10] Three airports: LAX, SFO, and DTW started their first nonstop flights to China in January 2000. We exclude them in the treatment group for model (1) but keeping them generates very similar results since they are always "treated."

dummies, such as the regional volume of imports from and exports to China; better long-run economic growth potentials which may not be fully captured by the set of year-month dummies; the international and domestic competition of airline industry. These imply that the direct flight areas are "selected" by some observables and unobservables. This selection creates an omitted variable bias in estimating equation (1). We proceed to estimate a standard DID model using the control group as a comparison to tease out these common, unobserved confounding factors. The model now is specified as

$$Y_{it} = \alpha_i + \beta_1 AfterDF_{it} + \beta_2 DirectFlightArea_i * AfterDF_{it} + \lambda_t + \varepsilon_{it}\ , \quad (3)$$

where *DirectFlightArea* is a dummy variable set to one if a county is located within a 150 mile buffer of an airport with at least one direct-flight to China and set to zero if a county is located within a 150 mile buffer of other top 60 airports without direct flight to China. The main effect of *DirectFlightArea* dummy variable is absorbed by county fixed effects. β_1 and β_2 are the key coefficients to be estimated and β_2 is the causal effect. To incorporate the possible serial correlation within a county, standard errors are clustered at the county level. The counties in the same flight area may be spatially correlated or generate mutual spillover effects, we also try to cluster the standard errors at the flight area levels. (A standard DID model requires a parallel trend before the policy change for both treatment and control groups. A tentative test for parallel trend is in the appendix.)

Although we can still specify Y_{it} as one of these six outcome variables, we separate the estimation for housing prices in the next subsection because we also want to understand the effect of Chinese homebuyers on local housing prices.

3.3 DID models for housing prices

It is straightforward to estimate the effect of nonstop flights on local housing prices by replacing the dependent variable in Model (3) by median housing price level or its logarithm:

$$Price_{it} = \alpha_i + \beta_1 AfterDF_{it} + \beta_2 DirectFlightArea_i * AfterDF_{it} + \lambda_t + \varepsilon_{it}. \quad (4)$$

Model (4) is the reduced form for estimating the effect of a decrease in the air travel cost between the US and China on local housing prices in the US counties. The underlying channel is that a decrease in the air travel cost between the US and China increases the number of homebuyers from the mainland China, which is estimated by Models (1)-(3). The natural question then is "what is the price effect of adding one more Chinese homebuyer to a local housing market?" That is, we are interested in estimating the following model:

$$Price_{it} = \alpha_i + \beta_1 NumberChineseBuyers_{it} + \lambda_t + \varepsilon_{it}, \quad (5)$$

where $NumberChineseBuyers_{it}$ refers to the total number of homebuyers from the mainland China in county *i* in month *t*. Model (5) is essentially a demand equation and cannot be estimated by a simple OLS regression because of simultaneity problem: the number of Chinese buyers obviously depends on the local housing prices. However, since launching a nonstop flight to China by an airport causes an increase in the number of Chinese homebuyers in a county close to the airport, this "policy shock" can serve as a good instrumental variable (IV) for the number of Chinese buyers, and therefore, Model (3) can serve as the first stage of the IV approach for estimating Model (5). This two-stage least squares (2SLS) regression or IV approach estimates the causal effect of Chinese homebuyers on local housing prices.

Theoretically, the causal effect of Model (5) using 2SLS can be derived by dividing the reduced form estimates from Model (4) divided by the first-stage estimate of from Model (3) (Angrist and Pischke, 2009).

3.4 Displacement effect

Existing studies have found that out-of-town real estate buyers push up local housing prices and push local residents to move out of high-quality neighborhoods (Cvijanovic and Spaenjers, 2017). To test whether Chinese homebuyers displace local residents, we estimate the following DID model taking advantage of variations in distance between a county and a major airport:

$$Y_{it} = \alpha_i + \beta_1 AfterDF_{it} + \beta_2 Distance_i * AfterDF_{it} + \lambda_t + \varepsilon_{it}, \quad (6)$$

where *Distance* variable refers to the distance between a county to a nearby major airport. In estimating Model (6), we use only the treatment group as we estimate Model (1). The estimates will show whether Chinese (local non-Chinese) buyers tend to locate in counties close to (further away from) a major airport after the airport launched a nonstop flight to China.

As a robustness check, we also extend Model (6) to including the control group. This is essentially a triple differences model:

$$\begin{aligned} Y_{it} = \alpha_i + \beta_1 AfterDF_{it} + \beta_2 DirectFlightArea_{it} * AfterDF_{it} \\ + \beta_3 Distance_i * AfterDF_{it} \\ + \beta_4 Distance_i * AfterDF_{it} * DirectFlightArea_{it} + \lambda_t + \varepsilon_{it}, \quad (7) \end{aligned}$$

where omitted main effect of $DirectFlightArea$ and some interaction terms are dropped due to collinearity. The coefficient of the triple interaction term, β_4, is the causal effect; for example, if β_4 is positive for non-Chinese buyers, it means that compared with counties located in non-direct-flight areas, after an airport launched a nonstop flight to China, local buyers in the direct-flight areas tend to buy houses in counties further away from the airport, suggesting a displacement effect on local residents.

4 Results

4.1 Before-and-after comparison

Table 3 reports the results of the before-and-after comparison using only treatment group, namely, Model (1). The first panel uses the policy dummy variable "*AfterDF*" and the second panel replaces the policy dummy variable by the number of nonstop flights.

In panel 1, Column (1) shows that compared with the period before a nonstop flight started, the monthly number of Chinese homebuyers in a county increased by 0.42 afterwards (the mean is 0.92 in the before period). Column (2) shows that the percentage of Chinese buyers among all buyers in a county increased by 0.04 percentage point (the mean of share Chinese buyers in the before period is 0.16%) but it is insiginicant. Column (3) shows that on average median housing prices in a county increased by about $5229 after a direct flight operates; or increased by about 1.24% (insignificant). Column (5) shows that effects on the monthly number of local non-Chinese buyers and on the number of Chinese American buyers are not significant. The insignificance possibly is due to a smaller sample size because we use only the treatment group.

Panel 2 shows that adding an additional nonstop route to China increases the monthly number of Chinese homebuyers in a US county, increases local housing prices (insignificant), and decreases the number of local non-Chinese buyers. Taken together, the results with statistical significance in both panels are consistent with the summary statistics pattern in Table 2. Since the sample sizes are relatively small in this before-and-after comparison, we rely mainly on the standard DID estimation.

(Insert Table 3 here)

4.2 Number of Chinese homebuyers

Table 4 reports the results of the standard difference-in-difference models, namely, Model (3). The coefficient of the interaction term, *DirectFlightArea*AfterDF*, is the causal effect we are interested in. Columns (1)-(3) in the top panel excludes the airports that launched their first nonstop flight in 2000 or 2014, the starting and the ending year of our housing data sample; these airports are included in the treatment sample in Columns (4)-(6). These two sets of results are pretty similar, so we focus on Columns (1)-(3).

Column (1) in the top panel shows that compared with the period before a nonstop flight started, the monthly number of Chinese homebuyers in a county increased by about 0.44 afterwards (the mean number of Chinese buyers for the full sample is 0.88); Column (2) further shows that the percentage of Chinese buyers among all buyers in a county increased by 0.12 percentage point (the mean of share Chinese buyers in the full sample is 0.17 percentage point). These results confirm that with the decrease in air travel costs between the US and China due to the opening of nonstop flights, more Chinese move from the mainland China to buy houses in the US counties that are located close to the airports with nonstop flights. Column (3) further show that the decrease in international air travel costs has no effect on the number of local Chinese American buyers, confirming that the increase of Chinese homebuyers indeed are from the mainland China, not from the US.

The bottom panel replaces the policy dummy variable (AfterDF) by the number of nonstop flights in each month each county, and the patterns of the results are similar.

(Insert Table 4 here)

4.3 Local housing prices

Table 5 reports the results for local housing prices using the same standard DID models as in Table 4. The top panel uses the median housing price level as the dependent variable, and the bottom panel uses its logarithm. Column (1) of the top panel shows that on average median housing prices in a county increased by about $5,865 after a direct flight operates; or increased by about 3.7% in Column (1) of the bottom panel. The other columns are robustness checks and show similar effects. Note that these models are considered reduced form and estimates the causal effect of a decrease in international air travel costs on local housing prices in US counties.

(Insert Table 5 here)

As a byproduct, we can also estimate how much local housing prices will increase due to an additional Chinese buyers entering a local housing market in a US county in a month. We report in Table 6 the results of estimating Model (5) using 2SLS. The first stage results are simply drawn from Table 4, and the second stage results are reported in the bottom panel of Table 6 using median price level as the dependent variable. Column (1) of the bottom panel shows that after one more Chinese buyer enters the local housing market, his or her transaction causes local housing price to increase by $16,306; this does provide empirical evidence for many news reports that Chinese real estate buyers push up local housing prices in big cities such as Los Angeles and Vancouver. Column (3) further show that increasing the proportion of Chinese buyers in the local markets by 0.1 percentage point (the mean is 0.17%) would raise the local housing prices by $6,021. Note that the F test statistics (three of four below 10) show that the instrument variables are likely weak, so we interpret these results as suggestive.

(Insert Table 6 here)

4.4 Displacement effect

Table 7 reports the results of estimating the effects of reduced air travel costs on number of local non-Chinese buyers. Columns (1) and (3) show that launching nonstop flights reduces the monthly number of local buyers by about 5 or 6 in a county although they are not statistically significant. Columns (2) and (4) show that launching an additional nonstop route to China reduces local buyers by 28 or 29 with statistical significance at the 1% level. These results, taken together, suggest that an increase in Chinese buyers, due to a decrease in international travel costs, crowds out local buyers, suggesting a displacement effect.

(Insert Table 7 here)

Table 8 provides more evidence on the displacement effects on local non-Chinese buyers. The top panel presents the results from estimating Model (6) and the bottom panel Model (7). Columns (1) and (2) show that although launching nonstop flights on average increase the number of Chinese buyers in a county, this effect attenuates with distance away from the airport: each additional 10 miles away from the airport decreases the number of Chinese buyers by 0.2; at the distance of 87 (42 based on Column (2)) miles away from the airport, there is no increase in the number of Chinese buyers.

The pattern for non-Chinese buyers is opposite: Columns (3) and (4) show that although launching nonstop flights on average decreases the number of non-

Chinese buyers in a county, this effect is offsetting with distance away from the airport: each additional 10 miles away from the airport increases the number of local non-Chinese buyers by 11; at the distance of 53~56 miles away from the airport, there is no decrease in the number of non-Chinese buyers. These suggest that local residents are pushed out to neighborhoods away from the airport while Chinese buyers tend to concentrate surrounding the airport. The bottom panel shows similar pattern.

(Insert Table 8 here)

What would cause the "displacement effect"? It could be the increased housing prices due to more Chinese buyers that drove some local non-Chinese moving out; it could also be the residential preference that non-Chinese people prefer to live with their same-ethnicity or same-race peers. In this study we cannot separate these two possible channels.

5 Conclusion

This paper tests how a decrease in international air travel costs affects the local housing markets. Specifically, using the CoreLogic housing transaction data and employing differences-in-differences models, we find that after a major American airport launched a nonstop flight to China, the monthly number of Chinese homebuyers in the counties nearby by the airport increased by 0.4 (the mean is 0.9) compared with the period before; the proportion of Chinese buyers among all buyers increased by 0.12 percentage point (the mean is 0.17); median housing prices increased by $5,865 or by 3.7%. These pieces of evidence suggest that a decrease in international travel costs between China and the USA increased the demand for housing in the USA cities due to increased Chinese migrants or investment demand. We also find that the local non-Chinese homebuyers significantly reduced, suggesting a displacement effect on local residents by "out-of-town" homebuyers.

Our study contributes to the literature on the social and economic impacts of air travel and "out-of-town" real estate buyers. Our study also has a more general implication in urban economics: the well-established spatial equilibrium mechanism within a city or across cities within a country can to a certain degree be applicable across countries.

References:

Angrist, J., Pischke, J.S., 2009, *Mostly Harmless Econometrics*, Princeton University Press.

Badarinza, C., Ramadorai, T., 2016, Home away from home? Foreign demand and London house prices. Working Paper.

Beane, Ashley Renee, 2007, Aviation relations between the United States and China: Are open skies on the horizons, Journal of Air Law and Commerce 72, 803-833.

Bel, G., Fageda, X., 2008, Getting there fast: globalization, intercontinental flights and location of headquarters, *Journal of Economic Geography* 8, 471–495.

Blonigen, B., Cristea, A., 2015, Air service and urban growth: Evidence from a quasi-natural policy experiment, Journal of Urban Economics 86, 128-146.

Brueckner, J., 1987, The structure of urban equilibria: a unified treatment of the Muth-Mills model, in *Handbook of Regional and Urban Economics*, volume 2 (E. Mills, edt), 821-845, North-Holland.

Brueckner, J., 2003, Airline traffic and urban economic development, *Urban Studies* 40 (8), 1455-1469.

Campante, F., Yanagizawa-Drott, D., 2016, Long-range growth: economic development in the global network of air links, NBER Working Paper No. 22653.

Catalini, C., Fons-Rosen, C., Gaule, P., 2016, Did cheaper flights change the direction of science? CEPR Discussion Paper No. 11252.

Chinco, A., Mayer, C., 2016, Misinformed speculators and mispricing in the housing market, *Review of Financial Studies* 29, 486–522.

Cvijanovic, D., C. Spaenjers, 2017, Real estate as a luxury good: non-resident demand and property prices in Paris, Working Paper University of North Carolina at Chapel Hill.

Ellis, J., Madureira, L., Underwood, S., 2016, The causal effects of proximity on investment: evidence from flight introduction, Working Paper.

Favilukis, J., Nieuwerburgh, S.V., 2017, Out-of-town home buyers and city welfare, Working Paper.

Fujita, M., Thisse, J.F., 2002, *Economics of agglomeration: cities, industrial location and regional growth*, Cambridge University Press, Cambridge, UK.

Lei, Zheng, Yu, Man, Chen, Ruowei, O'Connell, John, 2016, Liberalization of China-US air transportation market: assessing the impacts of the 2004 and 2007 protocols, Journal of Transport Geography 50, 24-32.

LeRoy, S., Sonstelie, J., 1981 Paradise lost and regained: transportation innovation, income, and residential location, *Journal of Urban Economics* 13, 67-89.

Redding, S., Turner, M., 2015, Transportation costs and the spatial organization of economic activities, in *Handbook of Regional and Urban Economics*, volume 5 (G. Duranton, V. Henderson, W. Strange, eds), 1339-1398, North-Holland.

Sá, F., 2016, The effect of foreign investors on local housing markets: evidence from the UK, CEPR Discussion Paper No.11658.

Yilmazkuday, D., Yilmazkuday, H., 2014, The role of direct flights in trade costs, Federal Reserve Bank of Dallas Globalization and Monetary Policy Institute Working Paper No. 179.

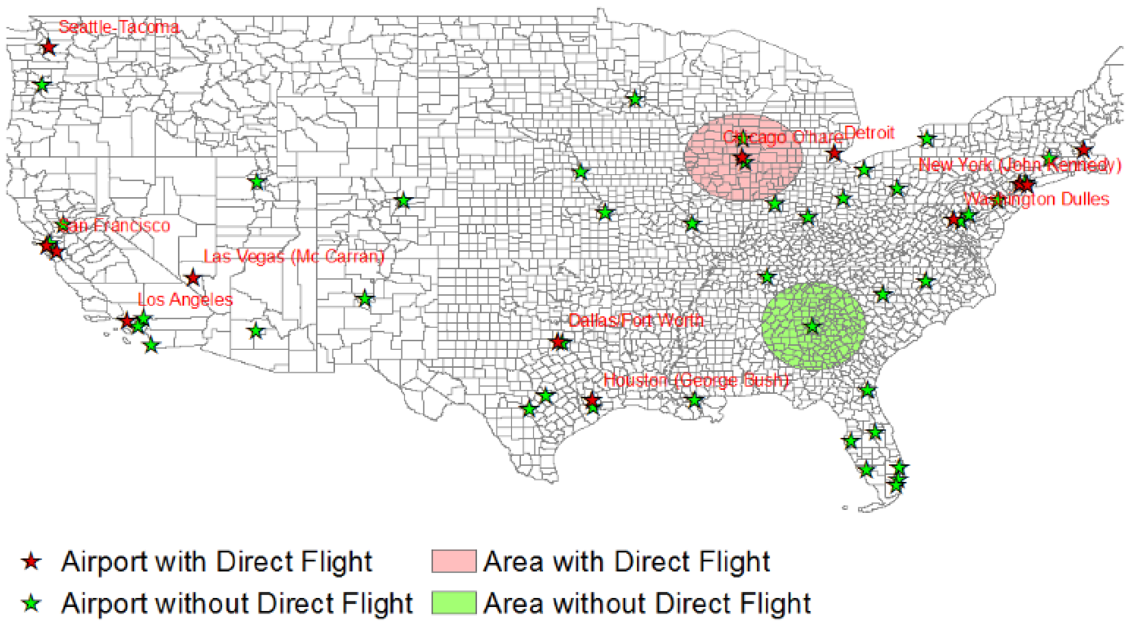


Figure 1: Counties and the top 60 airports

Note: A red star indicates an airport that has had at least one nonstop flight to China. A green star indicates an airport without any nonstop flight to China. The circle surrounding an airport is a 150 mile buffer area.

Table 1: List of airports with nonstop flights to China

US Airport	US County	Date	Chinese City
ATL	Atlanta, GA	March 2008	Shanghai
BOS	Boston, MA	June 2014	Beijing
		June 2015	Shanghai
DFW	Dallas/Fort Worth, TX	June 2014	Shanghai
		May 2015	Beijing
DTW	Detroit, MI	January 2000	Beijing
		April 2000	Shanghai
EWR	Newark, NJ	June 2005	Shanghai
		March 2009	Shanghai
IAD	Washington, DC	March 2007	Beijing
IAH	Houston, TX	August 2013	Beijing
JFK	New York, NY	September 2002	Beijing
		December 2006	Shanghai
		July 2015	Guangzhou
LAS	Las Vegas, NV	December 2016	Beijing
LAX	Los Angeles, CA	January 2000	Shanghai
		January 2000	Guangzhou
		November 2000	Beijing
ORD	Chicago, IL	April 2001	Beijing
		November 2004	Shanghai
SEA	Seattle, WA	March 2008	Beijing
		June 2013	Shanghai
SFO	San Francisco, CA	January 2000	Beijing
		January 2000	Shanghai
		June 2014	Chengdu
SJC	San Jose, CA	December 2010	Beijing
		March 2011	Beijing

Note. The nonstop flight between Atlanta and Shanghai ended in January 2012. Two direct flight airports (HNL at Honolulu, HI and ANC at Anchorage, AK) are not listed here.

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Full sample					
# of Chinese buyers from China	334,879	0.88	5.64	0	250
# of Chinese buyers from USA	334,879	0.69	3.83	0	320
# of non-Chinese buyers	334,879	151.77	398.75	0	14845
Median housing price ($)	334,879	95302.59	69749.29	72.69	1145588
Share of Chinese buyers	334,879	0.0017	0.0084	0.0	1.0
Treatment group before treated					
# of Chinese buyers from China	51,577	0.92	3.98	0	83
# of Chinese buyers from USA	51,577	0.85	3.72	0	320
# of non-Chinese buyers	51,577	190.41	424.92	0	7059
Median housing price ($)	51,577	103979.10	70739.13	167.41	993352.40
Share of Chinese buyers	51,577	0.0016	0.0062	0	0.31
Treatment group after treated					
# of Chinese buyers from China	49,184	1.68	6.86	0	239
# of Chinese buyers from USA	49,184	0.85	2.67	0	67
# of non-Chinese buyers	49,184	179.35	338.45	0	7332
Median housing price ($)	49,184	127539.30	80271.10	76.80	991240.60
Share of Chinese buyers	49,184	0.0039	0.0124	0	1
Control group before treated					
# of Chinese buyers from China	62,950	0.40	1.87	0	80
# of Chinese buyers from USA	62,950	0.40	1.48	0	141
# of non-Chinese buyers	62,950	163.00	370.07	0	5489
Median housing price ($)	62,950	88524.50	61898.25	171.17	1055773
Share of Chinese buyers	62,950	0.0010	0.0072	0	1
Control group after treated					
# of Chinese buyers from China	80,029	0.57	4.71	0	213
# of Chinese buyers from USA	80,029	0.46	3.13	0	121
# of non-Chinese buyers	80,029	130.17	467.23	0	14845
Median housing price ($)	80,029	84583.23	52604.00	72.6916	1145588
Share of Chinese buyers	80,029	0.0012	0.0072	0	1

Note. “Treatment group” refers to the counties that are located within a 150 mile buffer area surrounding an airport that has had at least one nonstop flight to China. “Before treated” and “after treated” refer to the time period before and after an airport launched the first nonstop flight to China, respectively. “Control group” refers to the countries that are located within a 150 mile buffer area surrounding a major airport that has so far never had a nonstop flight to China. The sample period is 2000~2014 and the observations are at the county-month level.

Table 3: The before and after comparison using treatment group

	#Chinese buyers from China	Share Chinese buyers	Median houisng price	Log(median housing price)	#Non-Chinese buyers	#Chinese buyers from USA
AfterDF	**0.4223***	0.0004	5228.7542*	0.0124	9.716	0.0319
	(2.11)	(1.59)	(1.93)	(0.51)	(0.81)	(0.38)
R^2	0.7139	0.3743	0.8178	0.7705	0.8701	0.6117
Sample size	100761	100761	100761	100761	100761	100761
# of direct flights	**0.1960****	0.0013***	1041.886	-0.0166	-28.6548***	-0.1964***
	(2.46)	(4.08)	(0.64)	(1.00)	(3.80)	(3.22)
R^2	0.7137	0.3785	0.8174	0.7707	0.8714	0.8082
Sample size	100761	100761	100761	100761	100761	122308

Note. The sample includes housing transactions completed during 2000 and 2014 and include only the treatment counties, the counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China. The observations are at the county-month level. All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust p-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Differences-in-differences models for number of buyers

	#Chinese buyers from China	Share Chinese buyers	#Chinese buyers from USA	#Chinese buyers from China	Share Chinese buyers	#Chinese buyers from USA
AfterDF	-0.0866	-0.0002	-0.0007	-0.4079	-0.0005	-0.0682
	(0.98)	(0.98)	(0.01)	(1.67)	(1.60)	(1.09)
DirectFlightArea*AfterDF	0.4390**	0.0012***	-0.0855	0.4150**	0.0012***	-0.0839
	(2.15)	(3.01)	(1.01)	(2.07)	(3.06)	(0.98)
R^2	0.6907	0.2573	0.6729	0.6998	0.2931	0.797
DF in 2000 or 2014	N	N	N	Y	Y	Y
Sample size	243739	243739	243739	265286	265286	265286
AfterDF	0.049	-0.0002	0.0217	-0.2504	-0.0005*	-0.036
	(0.38)	(1.06)	(0.38)	(0.99)	(1.70)	(0.53)
DirectFlightArea*#DF	0.1884***	0.0014***	-0.1393***	0.1127	0.0013***	-0.1535***
	(2.83)	(4.98)	(7.81)	(1.16)	(4.69)	(7.33)
R-squared	0.6906	0.2605	0.6732	0.6997	0.2953	0.7971
DF in 2000 or 2014	N	N	N	Y	Y	Y
Sample size	243739	243739	243739	265286	265286	265286

Note. The sample includes housing transactions completed during 2000 and 2014. The counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China during this period are the treatment group. The counties located within a 150-mile buffer of all other major airports are the control group. The observations are at the county-month level. "DF" refers to "direct flights". All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust p-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Differences-in-differences models for housing prices

	1	2	3	4
Meidan price				
AfterDF	864.2	2986.3	3958.6	5761.6**
	(0.56)	(1.63)	(1.6)	(2.46)
DirectFlightArea*AfterDF	5864.9*		5817.3*	
	(1.73)		(1.77)	
DirectFlightArea*#DF		1863.4		2405.6*
		(1.67)		(1.99)
R^2	0.7837	0.7835	0.8004	0.8004
DF in 2000 or 2014	N	N	Y	Y
Sample size	243739	243739	265286	265286
Ln(median price)				
AfterDF	0.0051	0.0230*	0.0311	0.0465**
	(0.34)	(1.92)	(1.42)	(2.55)
DirectFlightArea*AfterDF	0.0374**		0.0381**	
	(2.1)		(2.17)	
DirectFlightArea*#DF		0.0027		0.0084
		(0.3)		(0.9)
R^2	0.7494	0.7493	0.7592	0.7592
DF in 2000 or 2014	N	N	Y	Y
Sample size	243739	243739	265286	265286

Note. The sample includes housing transactions completed during 2000 and 2014. The counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China during this period are the treatment group. The counties located within a 150-mile buffer of all other major airports are the control group. The observations are at the county-month level. All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust *p*-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: 2SLS models for housing prices

	1	2	3	4
First stage				
Dependent variable	# of Chinese buyers		Share Chinese buyers	
AfterDF	-0.0866	0.049	-0.0002	-0.0002
	(0.98)	(0.38)	(0.98)	(1.06)
DirectFlightArea*AfterDF	0.4390**		0.0012***	
	(2.15)		(3.01)	
DirectFlightArea*#DF		0.1884***		0.0014***
		(2.83)		(4.98)
R^2	0.6907	0.6906	0.2573	0.2605
DF in 2000 or 2014	N	N	N	N
K-P F statistics	2.8	4.1	5.8	15.5
Sample size	243739	243739	243739	243739
Second stage				
Dependent variable: Median housing price				
#of Chinese buyers	16306.11*	14248.24**		
	(1.93)	(2.17)		
Share Chinese buyers			6020536***	1735727***
			(2.63)	(2.74)
DF in 2000 or 2014	N	N	N	N
Sample size	243739	243739	243739	243739

Note. The sample includes housing transactions completed during 2000 and 2014. The counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China during this period are the treatment group. The counties located within a 150-mile buffer of major airports that launched at least one nonstop flight to China since 2014 are the control group. The first stage models are drawn from Table 4. The observations are at the county-month level. All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust *p*-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Differences-in-differences models for number of non-Chinese buyers

	1	2	3	4
AfterDF	-1.45	9.56	1.38	12.41
	(0.11)	(0.86)	(0.09)	(1.04)
DirectFlightArea*AfterDF	-5.59		-5.23	
	(0.30)		(0.28)	
DirectFlightArea*#DF		-29.17***		-27.94***
		(4.45)		(4.30)
R^2	0.8832	0.8839	0.8841	0.8846
DF in 2000 or 2014	N	N	Y	Y
Sample size	243739	243739	265286	265286

Note. The dependent variable is the monthly number of non-Chinese homebuyers in a county. The sample includes housing transactions completed during 2000 and 2014. The counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China during this period are the treatment group. The counties located within a 150-mile buffer of all other major airports are the control group. The observations are at the county-month level. All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust *p*-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Displacement effect

	# Chinese buyers from China	# Chinese buyers from China	# of non-Chinese buyers	# of non-Chinese buyers
Treatment group only, DD				
AfterDF	1.6451**	0.7444	-63.0347	-59.323
	(2.85)	(0.9)	(1.81)	(1.58)
DistancetoAirport*AfterDF	-0.0190*	-0.0175*	1.1323**	1.1200**
	(2.29)	(2.20)	(2.79)	(2.81)
DF in 2000 or 2014	N	Y	N	Y
R^2	0.7166	0.7105	0.8721	0.8776
Sample size	100761	122308	100761	122308
Triple DD				
AfterDF	0.0989	-0.2297	-71.3109**	-68.2447*
	(0.86)	(0.91)	(2.05)	(1.93)
DF area*AfterDF	1.4978**	1.4366**	-6.8908	-6.3823
	(2.48)	(2.42)	(0.14)	(0.13)
DistancetoAirport*AfterDF	-0.0026**	-0.0025**	0.9918***	0.9891***
	(2.22)	(2.28)	(2.81)	(2.8)
DistancetoAirport*AfterDF*DFarea	-0.0170**	-0.0164**	0.1284	0.1262
	(2.14)	(2.06)	(0.24)	(0.24)
DF in 2000 or 2014	N	Y	N	Y
R^2	0.6925	0.7006	0.8846	0.8852
Sample size	243739	265286	243739	265286

Note. The sample includes housing transactions completed during 2000 and 2014. The counties located within a 150 mile buffer of the airports that launched at least one nonstop flight to China during this period are the treatment group. The counties located within a 150-mile buffer of all other major airports are the control group. The observations are at the county-month level. All models include county fixed effects and year-month fixed effects. Standard errors are clustered at the county level. Robust *p*-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

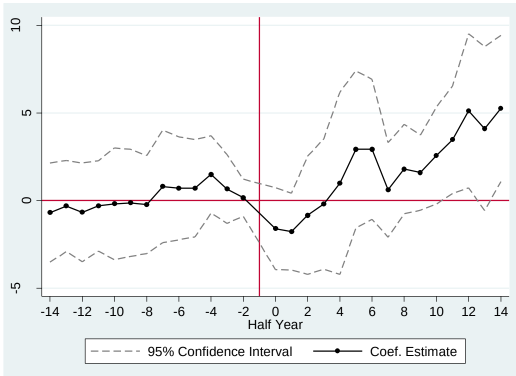
Appendix: (to be updated)

It is important to check the parallel trend for both treatment and control group before "treated." To do so, we estimate the following model:

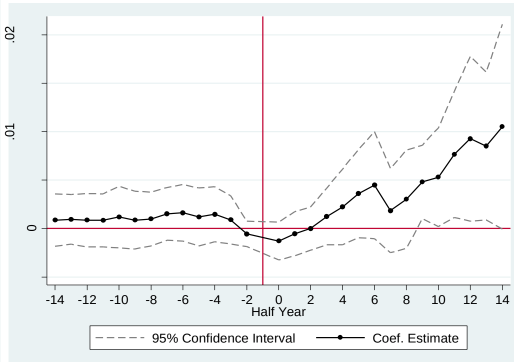
$$Y_{it} = \alpha_i + \sum_{h\in(-14,14)} \beta_h \, \tau_h DirectFlightArea_i * AfterDF_{it} + \lambda_t + \varepsilon_{it} \ .$$

For each half year, we create a dummy variable $\tau_h = 1$ if a county-month observation falls in the h^{th} half year window and assume the coefficient of the interaction term changes with each half year window. Figure A1 in the appendix presents the intuitive figures. Setting the month when an airport launched a nonstop flight to China as 0, we can track whether there is a systematically different trend between control and treatment groups. All the six graphs show that the coefficient of the interaction term is close to zero and not statistically significant for most of the half-year windows before the "treatment," demonstrating that the parallel trend holds between the control and treatment groups before "treated."

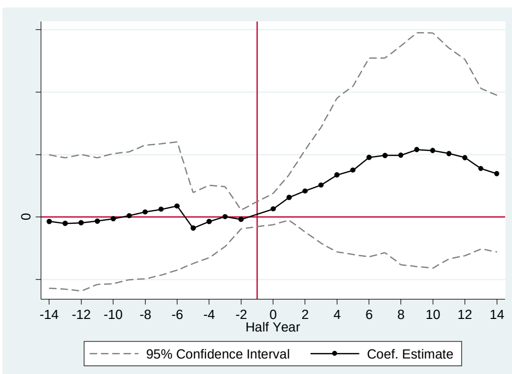
Figure A1: Testing the parallel trend for both treatment and control group before "treated"



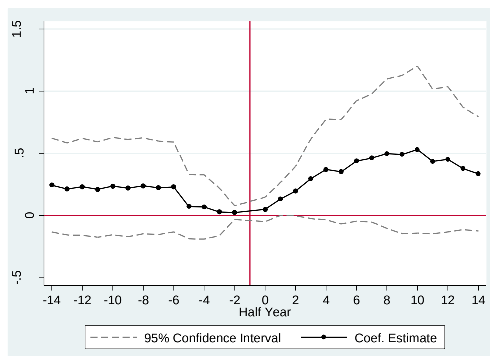
Number of Chinese buyers



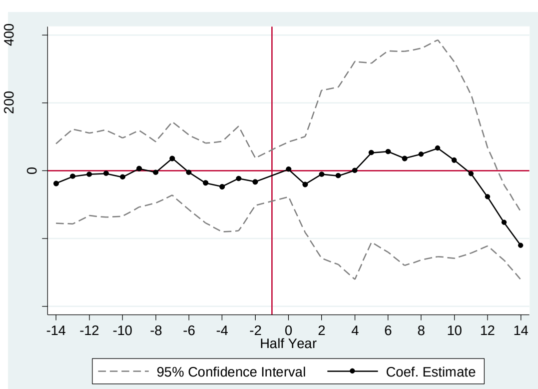
Percent of Chinese buyers



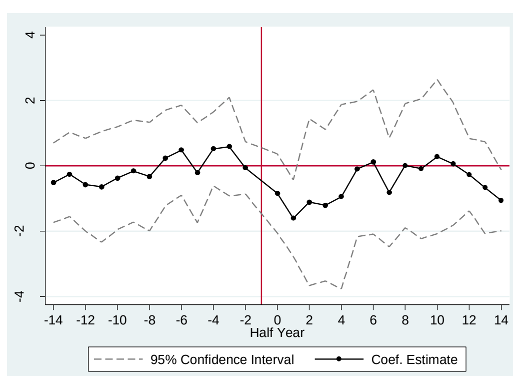
Median Housing Prices



ln(Median Housing Prices)



Number of non-Chinese Buyers



Number of Chinese buyers from USA