The Impact of U.S.-China Tensions on People Mobility

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The Impact of U.S.-China Tensions on People Mobility

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Abstract

Using novel monthly air passenger traffic data, we assess the impact of U.S.-China tensions on people inflows from China to the U.S. We find that there was a 6 percent decline in air passenger flows from China to the U.S. compared to other source countries during the period between 2017 and 2019. When differentiated by geographical locations, relative to other U.S. airports, U.S. airports near universities with a significant presence of Chinese students are found to have experienced a more than 10 percent annual drop in passengers originating from China. A further investigation reveals that the decline in people inflows is mainly attributed to the loss of passenger arrivals in August and that this decline is consistently more significant than the decrease experienced by airports near tourist destinations during the same period. These findings provide updated evidence of the detrimental effect a hostile political climate could have on international people mobility between two major scientific powers.

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International scientific and technological exchanges are inextricably intertwined with the economy, politics, and diplomacy. Looking back into history, from the *Coordinating Committee for Multilateral Export Controls* to its post-Cold War successor, the *Wassenaar Agreement*, and from the 40-year Japan-U.S. trade war (1950s–1990s) within the Western bloc to the mutual withdrawal of overseas students from China and the former Soviet Union in the 1960s, scientific cooperation and academic exchanges between nation states not only reflect their bilateral diplomacy, which is influenced by the political and economic development environment, but also have a significant impact on the development of international relations.

China and the United States are the two most important nation states today. Exchanges in science and education between the two countries have a long history and can be traced back at least to the late Qing dynasty. After the founding of the People's Republic of China in 1949, science and technology and higher education collaboration with the U.S. was disrupted until in the early 1970s after Nixon's visit to China. In fact, such collaboration became the earliest arena of Sino-U.S. cooperation. *The U.S.-China Agreement on Cooperation in Science and Technology* (1979), the very first formal government agreement between the two countries, launched a new era of top-down governmental collaboration. Since then, despite the ups and downs in their bilateral diplomacy, overall U.S.-China scientific and technological exchanges have sustained the momentum of growth. Yet starting from 2011, and especially since 2018, the growing tensions between the United States and China have become arguably the most dominant events in international politics. As the effects of the conflict start to unfold, the damages caused by the changing political climate between the two countries have also reached education and academic research arenas.[1]

Despite accumulating anecdotal evidence, no study to our knowledge has systematically investigated the impact of U.S.-China tension on bilateral people flow and scientific and educational exchange. Using a newly constructed dataset, we study the recent political tensions between two economic and scientific powers and estimate the effect of the deteriorating relationship of the two countries on people inflows from China to the United States.

Our findings enrich the literature on the consequences of political tensions. Existing studies detect negative effects of political conflicts on bilateral trade,[2] as well as on financial market performances.[3] Our research discloses that the damages caused by a worsening bilateral relationship also extend to people flows between countries. This study contributes by providing evidence of how a turbulent political climate between two countries affects international travels, particularly in the context of knowledge-intensive activities. It refreshes and adds to the accounts of the impact, at least indirect one, of skilled immigrants on knowledge production, drawing from historical political shocks, such as the diaspora of Soviet scientists,[4] as well as German Jewish émigrés in the United States.[5]

With another distinctive feature, this study combines highly disaggregated air traffic data with geographical feature of airports and universities, which enables explorations of useful variations at a granular level for a credible estimation of the short-term impact of political climate on people flows and education exchange. This supplements the commonly used bilateral migration data that is typically drawn from decennial censuses of national governments and thus is limited in both geographical coverage at the country-pair level, and the time frequency and timeliness of data.[6]

The rest of the paper proceeds as follows. The next section reviews three lines of related literature and proposes research questions for empirical investigations. Section 2 describes our research design and data. The empirical results are presented and analyzed in section 3. Section 4 concludes the article with a discussion on the limitations of this research, further directions, and policy remarks.

1. Literature Review and Research Questions

We identify three strands of literature relevant to our research: the drivers of the U.S.-China tension since 2018, its multi-dimensional impacts, and determinants of international travels.

a. Causes of Post-2018 U.S.-China Tension

Since the diplomatic relationship of the United States and China was established in 1979, the frictions and conflicts between the two counties have waxed and waned: the South China Sea disputes, arms sales to Taiwan, and the Trans-Pacific Partnership Agreement are just a few of these issues. But the ongoing U.S.-China trade war, beginning in 2018, is unique not only for its wide scope and scale but also the positions of involved parties. It started with tariff battle and soon escalated and embroiled bilateral scientific cooperation, technology markets, and talent mobility.

Scholars from different backgrounds have investigated the causes of this trade war. Some believe that the trigger is trade imbalance, and former U.S. President Donald Trump's intensifying disputes with China were sought to reduce the United States trade and fiscal deficits.[7] Some macroeconomists disagree. Stiglitz argued that the United States' low saving and tax cuts caused the Trump administration's alarming fiscal deficit.[8] As noted by Lai, reducing the trade deficit with China does not improve the United States' overall current account deficit in the era of globalization as other developing countries will sell similar goods to America.[9]

Another dominating view is that the then-Trump administration aimed to halt China's high-tech advancement and limit Chinese direct overseas investment for national security reasons. International relations scholars second this opinion. They posit that the United States' concern about its declining supremacy and China's rapid emergence as a challenger of U.S. hegemony catalyzed the U.S.-launched trade war.[10] This line of thinking is also popular among Chinese scholars.[11] The term "Thucydides Trap,"[12] indicating the inevitability of war between a declining superpower and a rising one, is adopted.[13]

Aligned with this international relation perspective, some scholars believe that Trump's goal of presidential reelection in 2020 was the reason for the trade war. Autor et *al.* found that Chinese exports led to unemployment and hardship for manufacturing workers in U.S. rural areas,[14] which mattered for Trump who had considerable support from the Midwest and motivated him to take a harder stance against China.[15]

b. Consequences of Escalating Tension between the United States and China

Undoubtedly, the escalating frictions between the two largest economies have far-reaching effects. Much research has examined the impact of the deteriorating relationship on U.S. prices, new automobile sales, welfare, foreign direct investment in both China and the United States, and the spillover effect on their trading partners, especially Asian economies.[16] The findings are rather consistent: the conflict would lead to a loss-loss situation for both sides. For instance, the *Financial Times* reports that the U.S. tariff battle with China cost American colleges considerable revenue.[17] According to the simulation by Itakura, the U.S.-China trade war would bring about a reduction of nearly all sectoral imports and outputs in both countries, and a 1.41 percent and 1.35 percent drop of the gross domestic product (GDP) in China and the United States, respectively.[18] He also asserts that the spillover effect of the U.S.-China trade war would account for a loss of 450 billion U.S. dollars in global trade.[19]

Not until recently has research explored if the U.S.-China scientific collaboration can weather the tempestuous political fallout. For example, based on evidence from joint publications and interviews, Woolston noted no influence of the U.S.-China tension on international scientific collaboration, while acknowledging the increasing difficulties of getting financial support for China-related work from the U.S. government.[20] Recent studies on a possible U.S.-China decoupling argued that, without intervention, the deteriorating relationship would wreak havoc on commercial and scientific bonds.[21] The China Initiative launched by the U.S. Department of Justice to prosecute certain U.S.-based ethnic Chinese science researchers and academics with links with Chinese research institutions,[22] the arrest of Meng Wanzhou, the then chief financial officer of Chinese telecommunications giant Huawei, the U.S.'s tightened visa scrutiny on Chinese students in science, technology, engineering, and mathematics (STEM), and its chokepoint strategy of sanctioning Chinese high-tech firms, to name just a few, are all expected to adversely affect the flows between the U.S. and China.[23] Though the aggregated statistics of people inflows and academic yearly enrolment data of international students and visiting scholars are available from the U.S. Department of Commerce and Institute for International Education (IIE) respectively, no study to our knowledge has rigorously examined whether and, if any, to what extent the intensifying U.S.-China conflict affected international travels, especially people inflows, nor has its impact on educational and academic exchange, controlling for other confounding factors, been established.

c. Determinants of International Travels

A variety of factors affect international travel and people flows. Most of this line of research is positioned in the field of tourism management and regional development. It has been largely accepted that supply and demand jointly contribute to the dynamics of international travel.[24] Demand factors of inbound tourism often include population, income, preferences, and expectations of inbound travelers and other features of their country of origin.[25] By contrast, supply factors of foreign flow often consist of characteristics of destination and arrival airports, such as cultural and natural capital, income per capita, hotel capacity, flight supply, environmental quality, agglomeration economies, and others.[26]

Regarding the effect of one-off events on international tourism, existing studies largely focus on global pandemics and disasters, such as the impact of avian flu, pandemic influenza, severe acute respiratory syndrome (SARS), and Covid-19 Pandemic on international tourism and Asian economies,[27] as well as the enduring deterrence of the Chernobyl nuclear accident on people inflows to Sweden.[28] Yet no research has empirically investigated whether a deteriorating bilateral relationship can significantly affect exchange activities between countries, while the post-2018 U.S.-China tensions, as a quasi-natural experiment, offer rare opportunities for an examination.

d. Research Questions

Integrating these three lines of literature, our study evaluates the impact of U.S.-China political climate on U.S.-bound people flows from China in general and on academic exchange in particular. Our empirical investigations can be summarized as being centered on two related research questions. The first one is about the impact on international travels in general:

Question 1: *How do the U.S.-China tensions affect people inflows to the U.S. differently between those from China and those from other origin countries?*

We expect to see that, other factors (i.e., demanding factors associated with country-of-origin and supply factors associated with destination and arrival airports) held constant, the U.S.-China political tensions more adversely affect inbound travelers from China than from other countries.

People travel internationally for a variety of reasons, including business, education or leisure. The U.S. has long been the most favorable destination for Chinese students and scholars to pursue their studies and research careers abroad. Considering the ongoing U.S.-China decoupling in science and technology, we propose the second research question that explores the destination heterogeneity associated with the expected impact in Question 1. It can be formulated as:

Question 2: *Is the negative effect of U.S.-China tensions on the people inflows from China stronger for knowledge-intensive destinations than for other destinations in the U.S.?*

In our empirical analysis we use the number of passengers destined for airports near university towns which are not popular tourist destinations as a broad measure or proxy of travels for knowledge-intensive activities. If there is an overall negative impact of the tensions as expected following Question 1, this second question takes one step further by asking how this impact varies with respect to the purpose of the visit (knowledge-intensive activities versus others).

2. Data and Methods

a. Data Description and Measurement

Our primary source of data is OAG, a globally leading air traffic database that covers more than 99 percent of scheduled flights worldwide. We retrieved the information on the monthly number of inbound passenger arrivals by each origin country and each destination airport in the United States.[29] The original data spans 84 months from January 2013 through to December 2019 (prior to the COVID-19 outbreak),[30] and covers international passenger flows from 228 countries or regions ending at 401 U.S. airports. The total number of observations is 2,145,262, where the unit of analysis represents a unique combination of an origin country (or region), a U.S. airport, and a year-month. For quality check, we benchmarked data against the official travel figures from the U.S. Department of Transportation.[31] Our original data is highly representative, accounting for 96 percent of total international air passenger arrivals in the U.S. for the period under study. Table 1 gives aggregate statistics of OAG data for international passenger arrivals in the U.S., distinguishing between those from China and from other countries, and also singling out those arriving at university-town airports. It can be seen that in contrast to the continued growth in passengers from other countries, passengers from China declined in 2019. This unique drop in Chinese travelers is even more prominent for passengers destined for university-town airports (defined as airports located within a 100-mile radius of a university with a significant presence of Chinese students in the U.S.), and the decrease started to happen in 2018.

Table 1: Number of International Passenger Arrivals in the U.S. (Thousand)

	From China	From all countries except China	From all countries except China, average	From China at U.S. university-town airports	From all countries except China at U.S. university-town airports	From all countries except China at U.S. university-town airports, average
2013	2,772	80,080	359	267	7,458	34
2014	3,180	89,795	399	307	8,632	40
2015	3,254	95,226	419	325	8,901	41
2016	3,696	101,542	453	375	9,497	43
2017	3,869	106,988	476	389	9,911	46
2018	3,954	110,894	486	377	10,390	48
2019	3,894	113,746	501	353	10,691	50

Source: Authors' calculation based on OAG.

One caveat with the OAG global air traffic data, as with all other international air traffic databases such as the International Civil Aviation Organization Aviation Data, is that it has no information about the travel purposes of passengers. Given this data limitation, to estimate the potential heterogeneous effects of U.S.-China tensions on people mobility, we adopt two surrogates to exploit systematic variations in destination features and seasonal travel patterns of these international travelers. The first one approximates the purpose of passenger inflows based on the distance of their destination airport from nearest universities and tourist cities, and the other one explores the differential impact on August, the peak arrival month for international students and scholars, relative to other months, to estimate the impact of U.S.-China tensions relevant to international education and academic exchange. It is reasonable to believe that if the changed U.S.-China relationship had a more significant implication on education and academic exchanges, the effect should be more pronounced for passengers with destination airports nearer to knowledge-intensive areas and arrivals in the months of August than the rest of the year.

The geolocation data of U.S. airports and their distances from the nearest universities and tourist cities are obtained from Google Maps. Table A1 (in appendices after the main body of this article) provides the names of U.S. universities with a significant number of Chinese students and Table A2 (in appendices) lists top U.S. tourist cities for Chinese visitors. The three categories of final destination airports are defined as follows:

University-town airports (treated group 1): Airports located within a 100-mile radius of a university with a significant presence of Chinese students but outside the 100-mile radius of any major tourist cities. Group size: 36 airports.

Tourist-city airports (treated group 2): Airports located within a 100-mile radius of a major tourist city but outside the 100-mile radius of any universities with a significant presence of Chinese students. Group size: 37 airports.

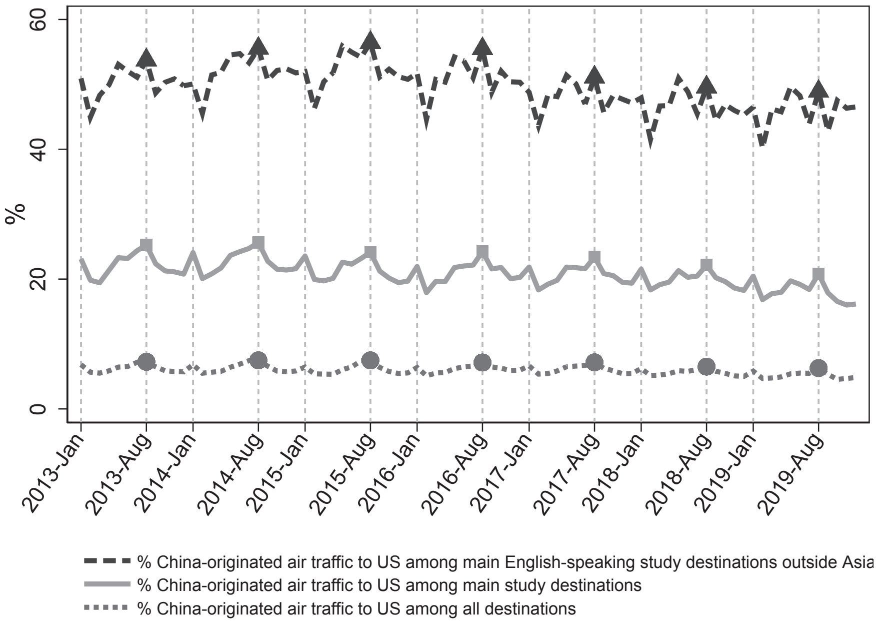
Airports that are neither of the above (reference group): airports located outside a 100-mile radius of any universities with a significant number of Chinese students and any major tourist cities. Group size: 285 airports.[32]

b. Descriptive Statistics

The first glance of the data reveals that though the United States has been one of the Chinese most favorite destinations for international travels despite the long distance, its popularity is declining.[33] As shown in Figure 1, the United States is losing its ground not only to other traditionally popular English-speaking countries outside Asia, but also to other destinations with a reputation in scientific research and education. As noted in existing studies, international travels, including education and research-oriented ones, are influenced by a variety of factors. Next, we adopt both difference-in-differences and difference-in-difference-in-differences estimation approaches to investigate whether or not and to what extent political tensions impacted people mobility from China to the U.S.

Table 2 describes the size and structure of the analytical samples, in which a unit of observation is the combination of an origin country, a U.S. airport, and a month in a year. In our baseline sample (sample A) where the 100-mile radius is used to define a university-town airport, we have around 23 thousand observations, only moderately less than the number of observations in the category of tourist-city airports, and about one sixth of those observations in neither of these two categories. Table 3 reports the key summary statistics of our baseline analytical sample. Here the number of passenger arrivals are converted to natural logarithms and the timespan is split into two periods: pre-2018 (i.e. 2016–2017) and post–2018 (i.e. 2018–2019). Comparing 2018–2019 with 2016–2017, it can be seen that passenger flow from China declined, which is in contrast to the growth of passengers from other countries. This pattern holds for all types of international arrivals.

Figure 1: Percentages of China-Originated Air Passengers Traveling to the United States.



Notes: "Main English-speaking destinations outside Asia" include the United States, the United Kingdom, Canada, Australia, and New Zealand. "Main study destinations" include the above countries plus Germany, Japan, and Singapore. "All destinations" include all travel destinations (223 countries or regions) with flights from China.

Source: Passengers data from authors' calculation based on OAG. The outbound flights from China in this study comprise departure flights from China excluding Taiwan and the two special administrative regions of Hong Kong and Macao.

Table 2: Size and Structure of Analytical Samples

Sample A (distance criterion: 100-mile radius)				
	University-town airports	Tourist-city airports	Non-university-town & non-tourist-city airports	University & airports
# Obs	229,059	272,281	1,322,618	321,304
# U.S. airports	36	37	285	43
# Origin countries	225	227	227	227
# Year-months	84	84	84	84
Sample B (distance criterion: 50-mile radius)				
	University-town	Tourist-city	Non-university-town & non-tourist-city	University & airports
	airports	airports	airports	
# Obs	138,260	219,823	1,579,052	208,127
# U.S. airports	16	25	339	21
# Origin countries	225	227	227	227
# Year-months	84	84	84	84
Sample C (distance criterion: 150-mile radius)				
	University-town	Tourist-city	Non-university-town & non-tourist-city	University & airports
	airports	airports	airports	
# Obs	269,373	322,820	1,112,481	440,588
# U.S. airports	48	43	240	70
# Origin countries	222	227	227	227
# Year-months	84	84	84	84

Notes: The unit of observation is a country-airport-year-month cell, where the country is the origin country and the airport is a U.S. destination airport.
Source: Authors' calculation based on OAG.

Table 3: Summary Statistics

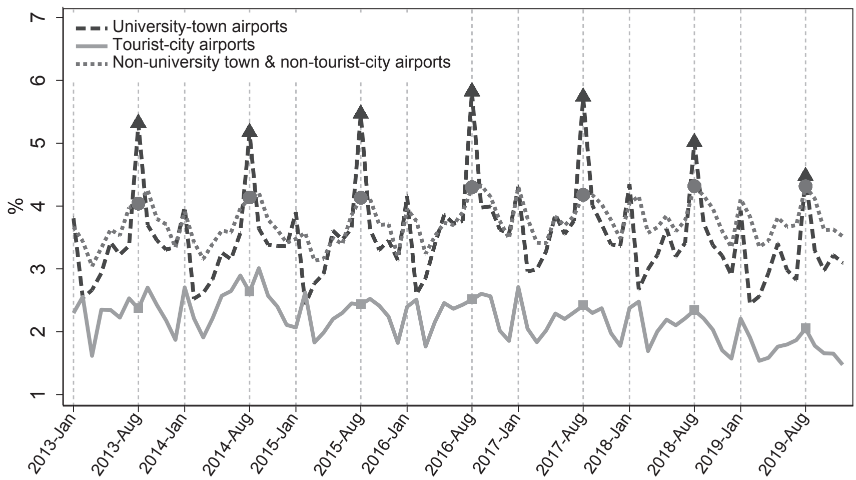
	China as origin country		Other countries as origin country	
	2016-2017 Mean(SD)[N]	**2018-2019 Mean(SD)[N]**	**2016-2017 Mean(SD)[N]**	**2018-2019 Mean(SD)[N]**
Ln # passenger arrivals	4.04	4.00	2.83	2.89
	(2.34)	(2.35)	(2.04)	(2.05)
	[6,414]	[6,516]	[605,415]	[606,617]
Ln # passenger arrivals at university-town airports	5.16	5.10	3.06	3.13
	(1.94)	(2.06)	(2.04)	(2.07)
	[633]	[625]	[64,592]	[64,069]
Ln # passenger arrivals at tourist-city airports	5.26	5.17	3.45	3.50
	(2.55)	(2.61)	(2.23)	(2.26)
	[636]	[645]	[77,305]	[77,393]
Ln # passenger arrivals at non-university-town & non-tourist-city airports	3.75	3.72	2.70	2.76
	(2.27)	(2.26)	(1.98)	(1.99)
	[5,145]	[5,246]	[463,518]	[465,155]

Notes: The whole data set consists of 228 origin countries, 401 U.S. arrival airports, and 84 months (January 2013 to December 2019). The first number reported in each cell is the mean, the second (in parentheses) is the standard deviation, and the third (in brackets) is the number of observations.

Source: Authors' calculation based on OAG.

Figure 2 plots the percentages of incoming passengers from China by the above categories of airports. Compared with the reference group (i.e., airports that are neither near a university nor a tourist destination popular with the Chinese) which shows a stable trend for the entire sample period, the decrease in the share of passengers from China becomes prominent after 2018, and is more so for university-town airports than for tourist-destination airports. Furthermore, these observed contrasts are starker for the peak travel month (August) than for other times of the year.

Figure 2: Percentages of China-Originated Passengers in All International Air Passenger Arrivals in U.S. Airports



Source: Authors' calculation based on OAG.

c. Estimation Strategy

Difference-in-Differences (DD) Approach

To control for the influence of other factors on people mobility, we start the estimation with a difference-in-differences (DD) framework, which can be expressed as:

$$\ln P_{ijym} = \alpha + \sum_{\substack{y=2013 \\ y\neq 2017}}^{y=2019} \beta^{y}\left(T_y * China_i\right) + \delta_{ij} + \omega_{ym} + \varepsilon_{ijym}, \tag{1}$$

where ln P_{ijym} is the log number of air passenger arrivals from country *i* in U.S. airport *j* in year *y* and month *m*; T_y denotes the year dummies with 2017 as the reference year; $China_i$ is the dummy for China as the origin country; δ_{ij} captures all influencing factors that are specific to a given pair of origin country and arrival airport such as geographical distance and number of universities near the destination; ω_{ym} captures time trends that are common to all observations, such as changes in U.S. or industry-level policies and seasonality in air traffic;[34] α is the intercept and Σ_{ijym} the estimation residual; and β*y*, the associated year-specific coefficient of the interaction term $T_y * China_i$, embodies the effect of U.S.-China tensions (when $y \geq 2018$) that is to be identified.

Intuitively, the DD design exploits variations within airport-time and within country-airport pairs, and estimates (i) the difference in the number of U.S. airport arrivals between passengers arriving from China (the treated group) and other countries (the reference group) in the base year (2017), and (ii) how the observed difference in (i) (if any) changes after 2018. A negative sign of βy for $y \geq 2018$ indicates a sharper drop in the passenger traffic from China than that from other countries.

Difference-in-Difference-in-Differences (DDD) Approach

As our main target of quest is the impact on knowledge-intensive destinations, a concern with βy is that a similar pattern could exist for other destinations that are neither close to a university nor a popular tourist city, in which case βy could be capturing an effect that was common to all airports. To improve the credibility of the estimate, we therefore use a difference-in-difference-in-differences (DDD) approach by adding a new comparison to Equation (1) to check the differential impact on university-town (or tourist-city) airports relative to airports that are distant from university and tourist destinations:

$$\ln P_{ijym} = \alpha + \sum_{\substack{y=2013 \\ y \neq 2017}}^{y=2019} \lambda^y \left(T_y * China_i * Treated_j\right) + \delta_{ij} + \theta_{iy} + \omega_{jym} + \varepsilon_{ijym}, \qquad (2)$$

where the new comparison comes from the triple interaction term $T_y * China_i * Treated_j$, in which $Treated_j$ is an added dummy for university-town (or tourist-city) airports; θ_{iy} is additional fixed effects controlling for country-year-specific confounding factors;[35] and λ^y is the key parameter to be estimated, allowing β^y in Equation (1) to differ between the treated and reference airports.[36] In this DDD design, a negative sign of λ^y for $y \geq 2018$ would indicate how, relative to the passenger arrivals at the reference airports and from origins other than China, the passenger arrivals at the treated airports from China are more adversely affected by the U.S.-China frictions. Compared to the DD design, this specification further explores variations across destinations with different levels of concentrations of knowledge creation activities, thus getting closer to the effect of interest.

3. Estimation Results

a. DD Estimation Results

The key estimated parameter β^y and its 95 percent confidence intervals for different specifications and subsets of airport are displayed in Figure 3 (also see columns (a) to (c) of Table A3 in appendices for the full estimation results). The result on all U.S. airports suggests a 6 percent drop in air passenger flows from China into the U.S. between 2017 and 2019, relative to other source countries in the same period as shown in the subfigure (a). This deeper drop in passengers from China combined with its timing is indicative of the impact of the tensions on people flows from China in general, thus consistent with our expected impact in Question 1. To put the estimated size of the impact in perspective, the number of passenger arrivals from China in the U.S. in 2017 was 3.9 million. The estimated effect of 6 percent drop is then equivalent to a loss of 234 thousand (i.e. 3,900,000*0.06) visits. Considering that the average number of arrivals in the U.S. from countries other than China stands at 475 thousand in 2017, the above drop amounts to a reduction of nearly half (234/475) of the number of international trips of an average country to the U.S.

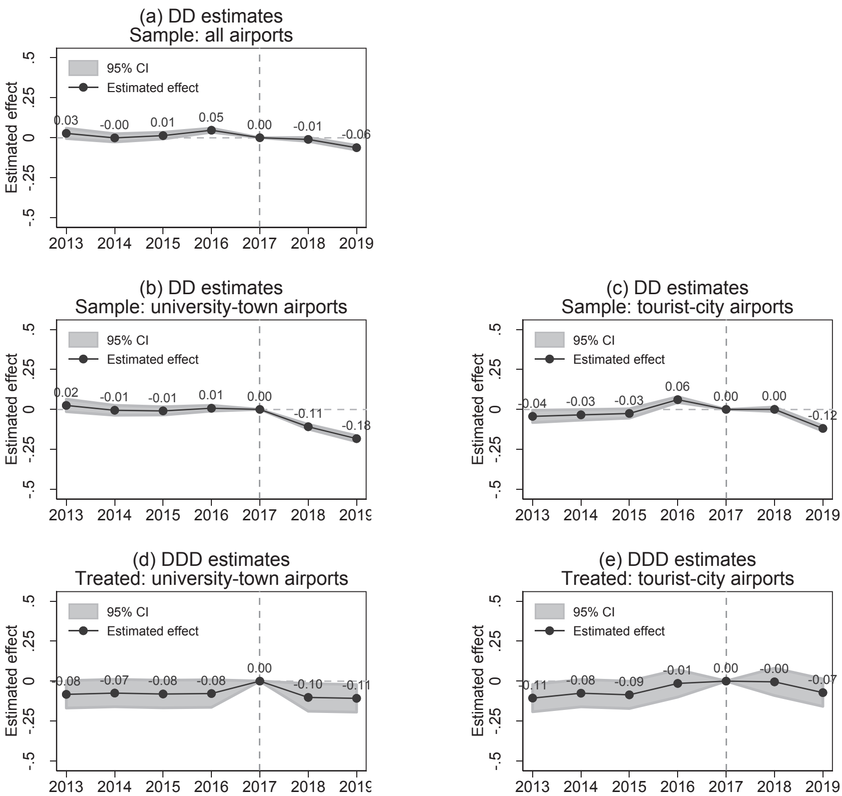
Subfigure (b) shows that the estimated effect of U.S.-China tensions on passenger arrivals in U.S. university-town airports is -11 percent in 2018 and dropped further down to -18 percent in 2019 at the significance level of 0.05. Again, to put the size of this effect in context, 389,000 trips were made from China to university-town airports in the U.S. in 2017. So the estimated effect amounts to a loss of 70 thousand (i.e. 389,000*0.18) trips from China to these knowledge-intensive destinations, which is about 1.5 (70/46) times the number of an average country's trips to the same destinations. In comparison, in subfigure (c) a negative effect is also found for passenger arrivals in tourist-city airports in 2019, but the size (12 percent) is smaller than that for university-town airports. This accords with our prediction regarding the effect on travels for knowledge-intensive activities in Question 2.

b. DDD Estimation Results

We add a third comparison to check the differential impact of the DD estimate for university-town or tourist-city airports relative to reference airports, following the strategy in Equation (2). We have two treated groups and one reference group of airports as defined previously: university-town airports (treated group 1), tourist-city airports (treated group 2), and airports that are neither a university-town nor a tourist-city airport (reference group). The subfigures (d) and (e) of Figure 3 visually display the DDD estimation results for λ^y of Equation (2) (also see columns [d] and [e] of Table A3 for the full estimation results). Indeed, we find a statistically differential effect for the two groups of treated airports relative to the reference group, with the magnitude in 2019 being -11 percent for university-town airport arrivals (subfigure [d] of Table A3). Benchmarked against the total size of the flow from China into the U.S. university-town airports in 2017, the magnitude of this effect amounts to a reduction of approximately 43 thousand (i.e. 389,000*0.11) visits from the country in a year. In contrast, the effect on tourist-city airport arrivals is not statistically different from zero. Again, the expectation following Question 2 is supported in this DDD estimation.

The fall semester of many U.S. universities starts in mid- or late-August, while international travel for business or sightseeing is often spread throughout the year. So we re-estimate Equation (2) with aviation data for August and for other months separately. This exercise is conceptually equivalent to a quadruple-difference design but parametrically less cumbersome. The results shown in Figure 4 support our expected impact in Question 2 (also see Table A4 in appendices for the full estimation results). For university-town airports, the estimated effects for 2018 and 2019 are -21 percent and -28 percent respectively (subfigure [a], statistically significant at the 5 percent level) for August arrivals, whereas that for other months is statistically insignificant (subfigure [b]). This nearly 20-plus-percentage-point difference suggests that for university-town airports August arrivals of passengers from China are indeed more adversely hit by the tensions than those in other months, providing further evidence about the scale of the negative impact of the U.S.-China tensions on academic inflows to the United States. For tourist-city airports, though the effect is -2 percent for August arrivals (subfigure [c]) and -7 percent for other months' arrivals (subfigure [d]) in 2019, and neither turns out to be statistically significant at conventional levels.

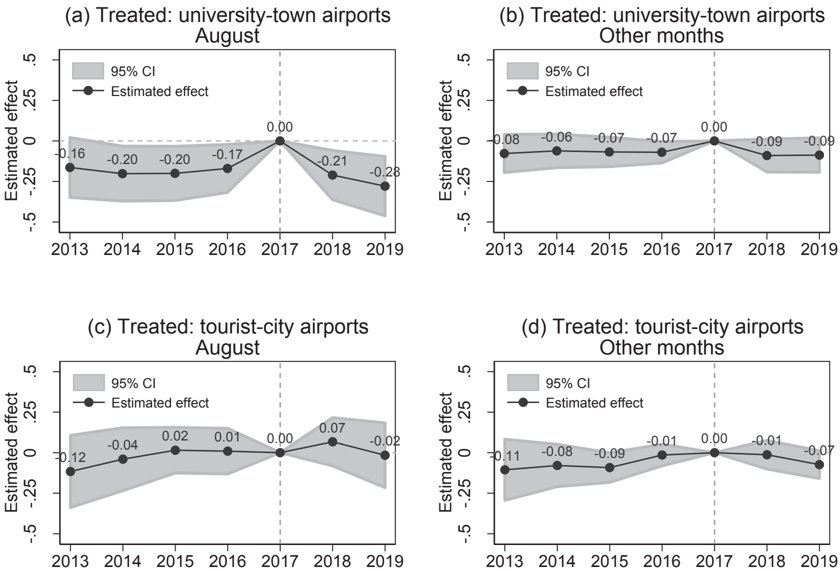
Figure 3: DD and DDD Estimates of the Effect of U.S.-China Tensions on Chinese Air Passenger Arrivals in All 401 Airports, 36 University-Town Airports, and 37 Tourist-City Airports in the U.S.



Notes: Estimated effect is extracted as the parameter βy, estimated from Equation (1), where 2017 is the reference year and countries other than China is the reference country group. Subfigures (d) and (e) display the DDD estimates of the effect of U.S.-China tensions on Chinese air passenger arrivals in 36 university-town airports and 37 tourist-city airports in the United States. Estimated effect is extracted as the parameter λ^y estimated from Equation (2), where 2017 is the reference year and countries other than China is the reference country group. In subfigures (d) and (e), the reference airports (285 airports) are those that are neither university-town nor tourist-city airports.

Source: Authors' calculation based on OAG.

Figure 4: DDD Estimated Effects of U.S.-China Tensions on Chinese Air Passenger Arrivals in University-Town and Tourist-City Airports in the U.S., August versus Other Months



Notes: Estimated effect is extracted as the parameter λ^y estimated from Equation (2) using a DDD strategy where 2017 is the reference year and countries other than China is in the reference country group. The treated airports are university-town airports (36 airports) in subfigures (a) and (b), and are tourist-city airports (37 airports) in subfigures (c) and (d). The reference airports (285 airports) are neither university-town nor tourist-city airports.

Source: Authors' calculation based on OAG.

c. Robustness Checks

For robustness checks, we adopt alternative definitions of a university-town or tourist-city airport in our estimate models. The distance criterion is changed from a 100-mile radius to a 50-mile or 150-mile radius. For university-town airports (Figure A2 in appendices), as expected, when the distance criterion becomes more relaxed (i.e. the distance cutoff is higher), the size of the estimated effect gets smaller as more distant airports are now included in the treated group that previously would have been in the reference group. August is invariably the worst affected month and is largely responsible for the overall negative impact estimated. A generally similar pattern exists for tourist-city airports (Figure A3 in appendices) when the distance cutoff is reduced to 50 miles, but the estimated effect for a 150-mile radius becomes statistically indifferent from zero. Table A5 (in appendices) contains the full estimation results.

In Figure A4 (in appendices), we conduct a before-after comparison in a DDD setting by clustering years into two periods: before or after 2018. The results offer a simple before-after contrast and are consistent with what has been estimated from the full-fledged model (see Table A6 in appendices for the full estimation results). Overall, relative to the pre-2018 period, Chinese passenger arrivals in U.S. university-town airports dropped by 11 percent after 2018, which is primarily driven by a sharp decline (25 percent) in August arrivals. For tourist-city airports, again, the negative effect is statistically and economically insignificant.

4. Conclusions and Discussions

a. Main Findings and Policy Implications

Using disaggregated passenger traffic data, this study reveals an uncomfortable and inconvenient truth about the impact of international politics on people mobility and knowledge flows across countries. It shows that the post-2018 U.S.-China tensions have already led to an alarmingly significant drop in the number of passengers traveling from China to knowledge-intensive destinations in the U.S., more than that is observed for air traffic from other countries and that for other U.S. destinations. Such a drop is found to exist robustly even after accounting for systematic differences across airports and sending countries, seasonality, and all possible interactions between factors along these dimensions. Our findings corroborate with the patterns from the recently released IIE data which show a similarly gloomy but less nuanced picture of the situation.

The sharp drop of China-originated people inflows is a reasonably good surrogate of the loss of Chinese students and scholars in the U.S. universities, which has implications far beyond financial hardship for some universities. Historically, the scientific supremacy of the United States has been deeply rooted in its capacity of tapping into the pool of global talent allowing the country to retain a significant number of U.S.-trained students, especially those at the highest-end who complete a PhD degree. On the one hand, in light of the high research productivity of Chinese PhD graduates in U.S. universities,[37] we expect that the reconsideration by young Chinese scientists of study and career locations away from the United States would lead to the decline of research productivity in U.S. institutions and enterprises where there has been a significant dependency on these academics for day-to-day research activities. [38] On the other hand, China's scientific leap forward has benefited from skilled returnees from the United States.[39] It will be an interesting avenue for future research to evaluate the incurred damage to knowledge production on both sides of the Pacific as well as beyond. Moreover, the less mobility of talent from China to the U.S., among other adverse factors, has led to the sharply decrease in the collaboration of scientists between both countries measured by the number of joint publications.[40]

b. Limitations and Future Research

Admittedly, this research is not without limitations. First, our identification comes from geographical and time variations, and thus the accuracy of our estimate depends partly on the measurement accuracy and how the reference groups are affected by the politico-economic tension. For instance, our measure for academic exchange assumes most enrolled student or visiting scholars fly to the nearest airport to their campus in August. Yet it is possible that they arrive at non-university-town airports, or academic personnel exchanges start in months other than August. Inbound passengers can also be returning Americans residing abroad and other non-Chinese nationals. For the U.S. universities with multiple campuses, we use the longitude-latitude information of their main campuses, possibly miscoding the airport for branch campuses and leading to an inaccurate estimate of impact.

Secondly, students and scholars from countries other than China may also have been affected, directly or indirectly, by U.S.-China tensions or other country-level factors correlated with them in two directions. On the one hand, as the U.S. domestic immigration policy and its relationships with the European Union and the Middle East also tightened or worsened during the same period as the U.S.-China trade war, a negative effect could also exist for passenger flows from these countries after 2018. However, as these origin countries are part of the reference group and are thus differenced out in our estimations, our estimated effect on China could be interpreted as a lower bound of the true effect. On the other hand, the fact that U.S. universities may expand their admissions of students and receive more researchers and academic visitors from other parts of the world to compensate for the loss of talent from China could lead to an overestimation of the impact on the inflows of Chinese passengers in the U.S.

Thirdly, this study only covers a relatively short time after the trade war. Although no evidence suggests that the tensions in the Sino-U.S. relations have substantially eased during the Biden area—in fact the rivalry has even worsened in certain areas including matters related to Taiwan and sanctions on advanced technology and parts—it would be useful to have an updated assessment of the impacts to incorporate more recent events.

In light of these limitations, several questions are worthy of further investigation. To begin with, it would be interesting to explore the spill-over effect of escalating U.S.-China tensions on China and other countries' international people flow. In this study, we only consider unilateral inbound flows from China and other countries to the United States. Future work could extend to explore how political tensions impact U.S.-origin passengers travelling to China, or multilateral business and tourism flows among different origin and destination countries.

Secondly, in addition to tertiary education, there has been an increasing number of Chinese students attending U.S. high schools. It would be interesting to check if they are less influenced by the tightened U.S. visa policy on China.

Thirdly, in this research the possible collateral damage of political tensions on tourist receipts are only checked very broadly in the background by looking at passenger arrivals at tourist cities. Subject to availability on more precise and geographically granular tourist data, future research could explore this impact more explicitly.[41] The year 2023 is the sixth of the simmering political tensions between the world's two largest economies. Because of the outbreak and rapid spread of COVID-19, suspension of flights between the U.S. and mainland China and travel warnings have delivered a heavier blow on top of U.S.-China tourism, academic exchanges and knowledge coproduction.[42] Their impacts, combined with the escalating Sino–U.S. rivalry, the ongoing war in Ukraine, the Chinese balloon incident and among others cast more turbulence and uncertainties on the global landscape of innovation and politics which could go far beyond what we expect.

Appendices

Table A1: List of top 25 U.S. Universities Recruiting Chinese Students

Rank (by # of F1 visas issued)	Name of university
1	University of Illinois Urbana-Champaign
2	University of Southern California
3	Purdue University
4	Northeastern University
5	Columbia University
6	Michigan State University
7	Ohio State University
8	University of California, Los Angeles
9	Indiana University
10	University of California, Berkeley
11	New York University
12	Pennsylvania State University
13	University of Minnesota
14	University of Washington Seattle
15	Arizona State University
16	University of Michigan Ann Arbor
17	Boston University
18	Illinois Institute of Technology
19	Rutgers, The State University of New Jersey
20	University of Texas at Dallas
21	University of Wisconsin-Madison
22	University of California, San Diego
23	Carnegie Mellon University
24	State University of New York at Stony Brook
	Syracuse University

Source: https://foreignpolicy.com/2016/01/04/the-most-chinese-schools-in-america-rankings-data-education-china-u/.

Table A2: List of U.S. Tourist Cities Most Popular with Chinese Visitors

Name of tourist city	Chinese characters
Atlanta	亞特蘭大
Baltimore	巴爾的摩
Boston	波士頓
Buffalo	水牛城
Chicago	芝加哥
Dallas	達拉斯
Detroit	底特律
Guam	關島
Hawaii	夏威夷
Honolulu	檀香山
Las Vegas	拉斯維加斯
Los Angeles	洛杉磯
Miami	邁阿密
Monterey	加州蒙特雷
New Orleans	新奧爾良
New York	紐約
Orlando	奧蘭多
Philadelphia	費城
Portland	波特蘭
Saipan	塞班島
Salt Lake City	鹽湖城
San Diego	加州聖地亞哥
San Francisco	舊金山
San Jose	加州聖荷西
Santa Barbara	聖巴巴拉
Seattle	西雅圖
Washington D.C.	華盛頓

Source: The list is based on compiled information from multiple leading Chinese providers of travel services including Ctrip, Qiongyou, and Mafengwo.

Table A3: Baseline DD and DDD Estimates, Dep. Var.: Log U.S. Airport International Air Passenger Arrivals (Unit of Observation: Country-Airport-Year-Month)

	DD estimates			DDD estimate	
	Sample: all airports	Subsample: university-town airports	Subsample: tourist-city airports	Treated airports: university-town airports	Treated airports: tourist-city airports
	(a)	(b)	(c)	(d)	(e)
T2013*China	0.027	0.025	-0.044		
	(0.020)	(0.024)	(0.024)		
T2014*China	-0.001	-0.005	-0.034		
	(0.016)	(0.019)	(0.020)		
T2015*China	0.013	-0.009	-0.025		
	(0.013)	(0.016)	(0.018)		
T2016*China	0.047	0.007	0.061		
	(0.008)	(0.011)	(0.011)		
T2018*China	-0.011	-0.108	0.000		
	(0.007)	(0.009)	(0.009)		
T2019*China	-0.063	-0.183	-0.119		
	(0.009)	(0.011)	(0.010)		
T2013*China*TreatedAirports				-0.083	-0.106
				(0.052)	(0.052)
T2014*China*TreatedAirports				-0.075	-0.076
				(0.052)	(0.052)

(Continued on next page)

T2015*China*TreatedAirports				-0.081	-0.086
				(0.052)	(0.052)
T2016*China*TreatedAirports				-0.078	-0.014
				(0.052)	(0.052)
T2018*China*TreatedAirports				-0.102	-0.005
				(0.053)	(0.052)
T2019*China*TreatedAirports				-0.108	-0.072
				(0.053)	(0.052)
Orig-dest FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	No	No
Orig-year FE	No	No	No	Yes	Yes
Dest-year-month FE	No	No	No	Yes	Yes
Obs	2,139,185	228,551	271,965	1,545,406	1,588,680
Adj. R^2	0.905	0.913	0.925	0.886	0.894

Notes: Time period: January 2013 to December 2019. Reference year (omitted): 2017. In the indicators of fixed effects (FE) used, "Orig" means departure country, and "dest" means destination airport in the U.S. Standard errors reported in parentheses are clustered by country (columns (a)–(c)) or country-airport (columns (d)–(g)). $^*p < .05$. $^{**}p < .01$. $^{***}p < .005$.

Table A4: DDD Estimates, August versus Other Months, Dep. Var.: Log U.S. Airport International Air Passenger Arrivals (Unit of Observation: Country-Airport-Year-Month)

	Treated airports: university-town airports		Treated airports: tourist-city airports	
	August	Other months	August	Other months
	(a)	(b)	(c)	(d)
T2013*China*TreatedAirports	-0.164	-0.078	-0.116	-0.106
	(0.112)	(0.071)	(0.135)	(0.115)
T2014*China*TreatedAirports	-0.202	-0.061	-0.040	-0.079
	(0.103)	(0.063)	(0.118)	(0.079)
T2015*China*TreatedAirports	-0.200	-0.068	0.015	-0.092
	(0.102)	(0.055)	(0.086)	(0.055)
T2016*China*TreatedAirports	-0.170	-0.070	0.009	-0.014
	(0.090)	(0.040)	(0.086)	(0.041)
T2018*China*TreatedAirports	-0.211	-0.090	0.067	-0.013
	(0.092)	(0.062)	(0.091)	(0.054)
T2019*China*TreatedAirports	-0.279	-0.087	-0.016	-0.074
	(0.111)	(0.064)	(0.122)	(0.052)
Orig-dest FE	Yes	Yes	Yes	Yes
Orig-year FE	Yes	Yes	Yes	Yes
Dest-year-month FE	No	Yes	No	Yes
Obs	132,685	1,405,930	135,784	1,446,226
Adj. R^2	0.902	0.887	0.908	0.895

Notes: Time period: from January 2013 to December 2019. Reference year (omitted): 2017. Standard errors reported in parentheses are clustered by country-airport. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .005$.

Table A5: Robustness Checks I—Alternative Definitions of University-Town and Tourist-City Airports, Dep. Var.: Log U.S. Airport International Air Passenger Arrivals (Unit of Observation: Country-Airport-Year-Month)

	(A) Treated airports: university-town airports					
	Radius: 50 miles			**Radius: 150miles**		
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
T2013*China*TreatedAirports	-0.030	-0.028	-0.031	0.029	-0.078	0.035
	(0.074)	(0.129)	(0.074)	(0.084)	(0.136)	(0.083)
T2014*China*TreatedAirports	-0.108	-0.186	-0.101	-0.014	-0.123	-0.002
	(0.066)	(0.121)	(0.069)	(0.078)	(0.126)	(0.078)
T2015*China*TreatedAirports	-0.088	-0.196	-0.079	0.008	-0.126	0.022
	(0.053)	(0.112)	(0.052)	(0.057)	(0.112)	(0.057)
T2016*China*TreatedAirports	-0.070	-0.100	-0.069	-0.012	-0.099	-0.005
	(0.033)	(0.100)	(0.032)	(0.044)	(0.098)	(0.043)
T2018*China*TreatedAirports	-0.097	-0.178	-0.091	-0.079	-0.184	-0.071
	(0.035)	(0.157)	(0.033)	(0.057)	(0.109)	(0.057)
T2019*China*TreatedAirports	-0.129	-0.247	-0.118	-0.075	-0.168	-0.065
	(0.052)	(0.089)	(0.054)	(0.058)	(0.113)	(0.057)
Orig-dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Orig-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest-year-month FE	Yes	No	Yes	Yes	No	Yes
Obs	1,710,478	146,918	1,556,091	1,376,156	118,163	1,251,919
Adj. R^2	0.886	0.901	0.887	0.884	0.901	0.885

	(B) Treated airports: tourist city airport					
	Radius: 50 miles			**Radius: 150miles**		
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
T2013*China*TreatedAirports	-0.108	-0.061	-0.111	-0.033	-0.036	-0.033
	(0.151)	(0.167)	(0.151)	(0.103)	(0.130)	(0.105)
T2014*China*TreatedAirports	-0.124	-0.126	-0.121	0.005	-0.011	0.008
	(0.094)	(0.120)	(0.095)	(0.079)	(0.107)	(0.080)
T2015*China*TreatedAirports	-0.122	-0.091	-0.122	-0.039	0.006	-0.041
	(0.065)	(0.074)	(0.068)	(0.052)	(0.086)	(0.053)
T2016*China*TreatedAirports	-0.059	0.058	-0.068	0.022	0.090	0.017
	(0.039)	(0.069)	(0.043)	(0.040)	(0.093)	(0.042)
T2018*China*TreatedAirports	-0.084	-0.002	-0.091	0.039	0.116	0.028
	(0.027)	(0.079)	(0.026)	(0.047)	(0.112)	(0.048)
T2019*China*TreatedAirports	-0.095	-0.143	-0.089	0.108	0.206	0.100
	(0.055)	(0.100)	(0.054)	(0.071)	(0.131)	(0.068)
Orig-dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Orig-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest-year-month FE	Yes	No	Yes	Yes	No	Yes
Obs	1,791,903	153,511	1,630,856	1,429,801	122,009	1,301,904
Adj. R^2	0.893	0.907	0.894	0.896	0.910	0.896

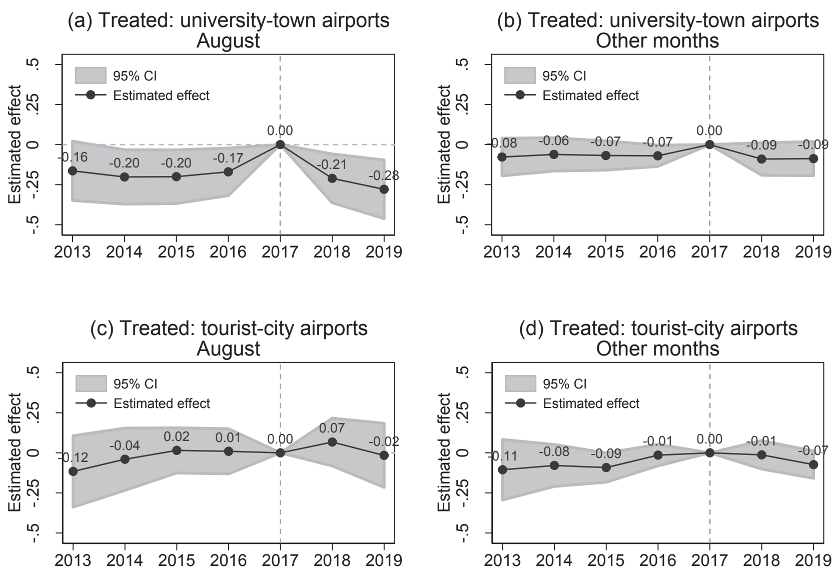
Notes: Time period: January 2013 to December 2019. Reference year (omitted): 2017. Standard errors reported in parentheses are clustered by country-airport. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .005$.

Table A6: Robustness Checks II—Clustering Years, Dep. Var.: Log U.S. Airport International Air Passenger Arrivals (Unit of Observation: Country-Airport-Year-Month)

	Treated: university-town airports			Treated: tourist-city airports		
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
Post2018*China*Treated Airports	-0.113	-0.253	-0.096	-0.030	0.015	-0.033
	(0.030)	(0.096)	(0.063)	(0.029)	(0.093)	(0.030)
Orig-dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Orig-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	656,962	52,438	597,652	676,881	53,936	616,089
Adj. R^2	0.895	0.914	0.896	0.904	0.922	0.905

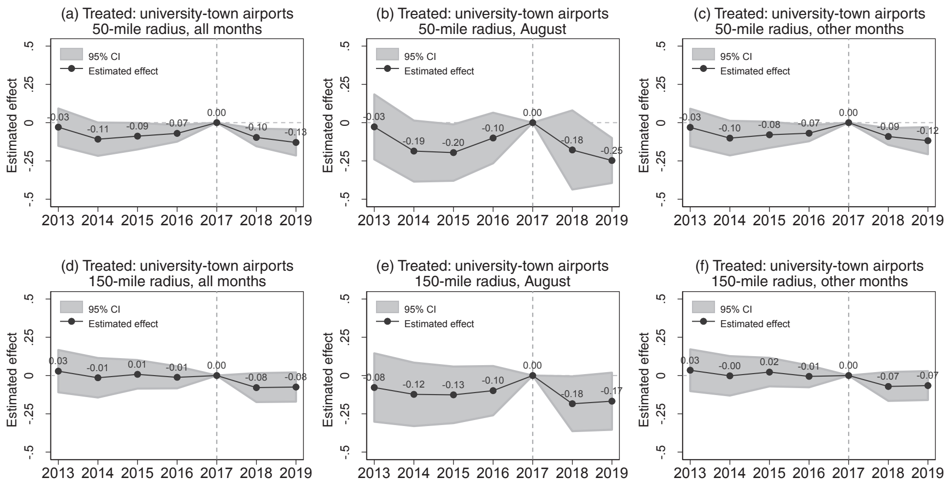
Notes: Time period: January 2013 to December 2019. Reference year (omitted): 2017. Standard errors reported in parentheses are clustered by country-airport. *$p < .05$. **$p < .01$. ***$p < .005$.

Figure A1: Location of the Three Categories of Airports in the Research



Notes: University-town airports (36 airports) are defined as airports located within a 100-mile radius of a university with a significant presence of Chinese students but outside the 100-mile radius of any major tourist cities. Tourist city airports (37 airports) are defined as airports located within a 100-mile radius of a major tourist-city but outside the 100-mile radius of any universities with a significant presence of Chinese students. Non-university-town and non-tourist-city airports (285 airports) are defined as airports located outside the 100-mile radius of any universities with a significant number of Chinese students and any major tourist cities.

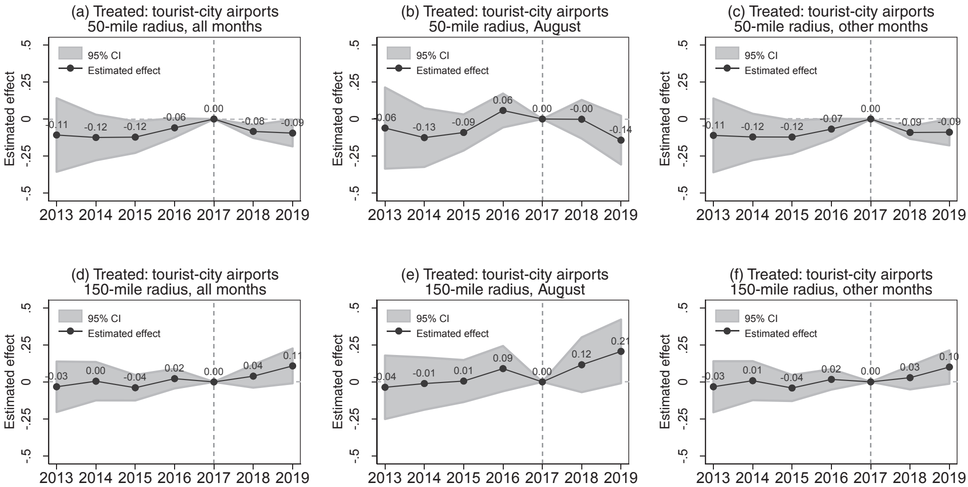
Figure A2: Robustness Checks I (a)—Alternative Definitions of University-Town Airports.



Notes: Estimated effect is extracted as the parameter λy estimated from Equation (2) using a DDD strategy where 2017 is the reference year and other countries than China are the reference country group. The treated airports are university-town airports (16 airports in subfigures (a), (b), and (c); 48 airports in subfigures (d), (e), and (f)). The reference airports are those that are neither university-town nor tourist-city airports (339 airports in subfigures (a), (b), and (c); 240 airports in subfigures (d), (e), and (f)). Definitions of these airports follow the text or Figure 3 except that the distance criterion is now 50-mile radius in subfigures (a), (b), and (c), and 150-mile radius in subfigures (d), (e), and (f). See Table A5 for the full estimation results.

Source: Authors' calculation based on OAG.

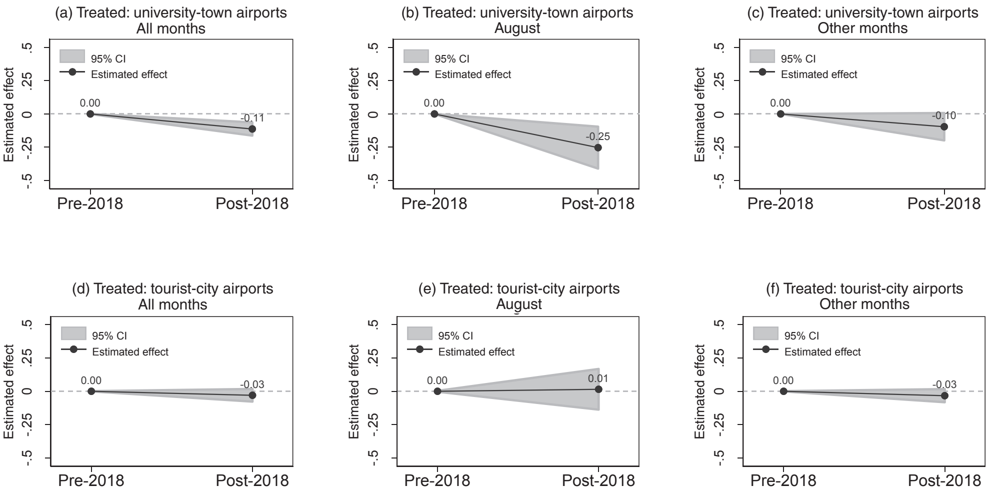
Figure A3: Robustness Checks I(b)—Alternative Definitions of Tourist City Airports



Notes: Estimated effect is extracted as the parameter λy estimated from Equation (2) using a DDD strategy where 2017 is the reference year and other countries than China are the reference country group. The treated airports are tourist city airports (25 airports in subfigures (a), (b), and (c); 43 airports in subfigures (d), (e), and (f)). The reference airports are those that are neither university-town nor tourist-city airports (339 airports in subfigures (a), (b), and (c); 240 airports in subfigures (d), (e), and (f)). Definitions of these airports follow the text and Figure 3 except that the distance criterion is now 50-mile radius in subfigures (a), (b), and (c), and 150-mile radius in subfigures (d), (e), and (f). See Table A6 for the full estimation results.

Source: Authors' calculation based on OAG.

Figure A4: Robustness Checks II—Clustering Years for a Before-After Comparison



Notes: Estimated effect is extracted as the parameter λ^y estimated from a modified version of Equation (2) using a DDD strategy where T^y is replaced by a period dummy, *post*2018, which takes on the value of one when *y*2018 and zero otherwise. Countries other than China are the reference country group. The treated airports are university-town airports (36 airports) in subfigures (a), (b), and (c), and are tourist city airports (37 airports) in subfigures (d), (e) and (f). In all subfigures, the reference airports (285 airports) are those that are neither university-town nor tourist-city airports. See Section 2-b for the exact definitions of these airports and Table A6 for the full estimation results.

Source: Authors' calculation based on OAG.

Notes

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29 The dataset allows us to distinguish between transfer and destination airports. In this research, all airports are destination airports of arrival.

30 Our air traffic data, which is a proprietary database, only covers the period till the end of 2019. However, the focus on this period, instead of more recent years, can also be justified by the pandemic of COVID-19 since early 2020 which was the dominant factor that significantly changed the patterns of global travel at least in 2020 and 2021. With travel restrictions/outright bans and health measures imposed on international travelers by many countries around the world, COVID-related policies and health concerns have distorted the normal patterns of international passenger flows. Even if data on more recent years is available, it would be heavily contaminated by the above factors, making it difficult to isolate the impact of geopolitical events from the impact of the pandemic, thus unsuitable for the purpose of this study.

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tourists. These 43 U.S. airports in total account for around 48 percent of international passenger arrivals and 67 percent of China-originated passenger arrivals. The loss of these large airports, however, should not be a major concern in this DDD setting as our estimation is based on airport-time and country-airport variations. In addition, the robustness of the distance criterion used is checked later where we change the distance criteria from 100 miles to 50 or 150 miles and the results remain qualitatively stable. Figure A1 in the Appendix section plots the locations of these university-town and tourist city airports. Figure A2 demonstrates the monthly China-originated passengers to the U.S. by different types of airports.

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