The Effect of International Travel on the Spread of COVID-19 in the U.S.

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Abstract

We examine the relationship between incoming international passengers and COVID-19 case or death counts during the first wave of the pandemic in the U.S. We find passengers from Italy, but not China, were an important source of exposure, and thus increased the early spread of COVID-19 in the U.S. These results suggest stopping travel from Europe earlier likely would have had greater impact on reducing the spread of the virus in the US, compared to the earlier ban on travel from China. Further, banning travel from pandemic hotspots may be smart policy, depending on the specific characteristics of the virus.

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1. Introduction

As the COVID-19 pandemic spread globally, a clear pattern of geographic heterogeneity emerged. In the United States, some locations, such as New York City, were hit very hard early on. Other locations, such as Dallas Texas, were hit very mildly early on, with increased severity months later.

Epidemiological models suggest two main sets of factors that affect geographic variation in virus outcomes: Exposure and environmental factors. For any location, international travelers arriving from COVID-19 hotspots represent a source of exposure to the virus. In contrast, environmental factors including population size and density, use of public transportation, air pollution, demographics, local policies, local economic activity, affect the virus's spread and impact once it has entered a location (e.g., Adda 2016, Clay et al. 2019).

Given the consensus that the virus originated in Wuhan, China, it would seem obvious, that at least during some very early period, incoming international passengers, specifically from China, brought the virus to the US. Indeed, on January 21, 2020, a Washington state man who had recently returned from Wuhan, China, became the first confirmed coronavirus case in the US. Within weeks, the first cluster of cases was identified in Washington State, including an outbreak at a nursing home which resulted in at least 37 deaths.

However, in February 2020, Italy experienced a major outbreak. Shortly thereafter, the center of the epidemic in the US shifted from the West Coast to the East Coast, causing epidemiologists to pay more attention to Europe, and especially, Italy as a source of infections. Validating this shift in focus, researchers began to provide evidence that the outbreaks on the East Coast appeared to result more from exposure to individuals from Italy than from China. One study showed that the strain of virus in New York City was the same strain as one circulating in Europe, but different from the strain in China (Gonzalez-Reiche et al., 2020).

US federal policy response to the Coronavirus focused on limiting exposure to international travelers. On January 31, President Trump announced a ban on entry into the US by most non-US residents traveling from China or who had recently visited

China. On March 11, President Trump imposed similar restrictions on travel from Europe.[2]

These travel bans were highly controversial, with some arguing that they were an unnecessary restriction on travel, while others have argued that by waiting until mid-March to shut down travel from Europe, the US allowed travelers from Europe to bring the virus to the US in large numbers, and that this greatly accelerated the spread of the virus, especially on the East Coast. Governor Cuomo of New York succinctly captures this view, saying that the US "closed the front door with the China ban, which was right. But we left the back door open" (Armstrong, et al., 2020). The authors argue that the influx of travelers from Europe, particularly from Italy, caused the outbreak in New York City[3]. Supporting this view, more than 1.8 million travelers arrived from Europe during February 2020 (Miller et al., 2020).

Despite these claims, the contribution of international travel restrictions to the spread of the virus in the US is still not well understood. The little extant research finds limited effects of travel restrictions (Chinazzi et al., 2020; Russell et al., 2020). More broadly, it is still not clear to what extent travelers from COVID-19 hotspots, specifically China and Italy, were important sources of early exposure to the virus in the US.

In this paper, using a model that accounts for key variables affecting exposure and environment, we address the following question: How much of the variation in the early spread of the virus across the US can be explained by airline travelers arriving from China and Italy?

Our empirical analysis examines the relationship between the number of airline passengers from Italy or China arriving in a particular county[4] during either the fourth quarter of 2019 or the first quarter of 2020, and the number of COVID-19 cases or deaths

[2] The ban on travel from China took effect on February 2, while the ban on travel from Europe took effect March 13. The latter ban was limited to the 26 countries that comprise the Schengen Area: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, and Switzerland.

[3] Buttressing this claim is genetic research that shows that one strain of the virus emerged directly from China, with this strain being found primarily in Washington State, within the US. But a second branch of the virus was brought from Italy, and this branch was more widely prevalent in New York City.

[4] Although we only observe passenger arrivals at the MSA level, we assign passengers to counties within the MSA based on the county's share of the MSA's population. We discuss this further below.

in the county by the approximate end of the first wave in the U.S. (May 31). To more precisely identify the effect of arriving international travelers, we divide passengers into three groups: (1) those arriving from China; (2) those arriving from Italy; and (3) those arriving from regions that experienced very little COVID-19 transmission in late 2019 and early 2020 – Central and South America, Africa, and the Middle East. We use passenger arrivals from destinations with very few or no confirmed infections to control (or proxy) for other factors that are correlated with both incoming international travelers and the spread of COVID-19.

We find two key results. Counties that received more passengers from China did not experience higher infection and fatality rates; in fact, both outcomes were lower. At the same time, counties that received more passengers from Italy experienced higher infection and fatality rates. Specifically, each additional 100 passengers from Italy arriving in a given county increased case (death) rates by about five percent. Importantly these results hold when controlling for passengers arriving from the three regions with little COVID-19 transmission, leaving only the (unlikely) scenario that there are unobservables that are correlated with Italian passengers, but not with passengers from the three regions with low COVID-19 transmission biasing our results.

Our findings are important in terms of looking back to understand the source of the epidemic in the US; however, they also have important policy implications for future viral epidemics, or even new strains of COVID-19 (Woodyatt et al., 2020). They suggest that stopping travel from Europe earlier likely would have had greater impact on reducing the spread of the virus in the US, compared to the relatively early ban on travel from China. Nonetheless, perhaps more importantly, these results suggest that banning travel from pandemic hotspots may be smart policy, depending on the specific characteristics of the virus.

2. Theoretical Framework

In this section, we provide a basic framework to guide the empirics that follow. We start by presenting a simplistic formula for the total number infected in a region

(Chowell et al., 2017; Allain, 2020)[5]. We then highlight, within our formula, the channels through which exposure and environmental factors would likely impact regional infections.

We consider the following basic formula for total infections in a given region at the early stages of viral spread:

(1) $N(t) = N(0) * (1 + a)^t$

where: $N(t)$ is the total number of infections in the region as of time t; $N(0)$ is the total number of infections in the regions at some initial time, $t = 0$; and a is the infection rate.

This formula is based on a simple dynamic, where the number of infections in a given period (N_t) is equal to the number of infections in the prior period (N_{t-1}) plus the number of new infections, calculated as the infection rate multiplied by the number of infections ($a*N_{t-1}$). Based on that simple dynamic, we arrive at formula (1) for the total number of infections at time t, starting from time 0.

If we assume a constant death rate (k), and some constant lag, say L, between infection and death, we have a similar formula for total deaths:

(2) $D(t + L) = k * N(0) * (1 + a)^t$

We now consider how and where exposure and environmental factors are likely to manifest within the above formulas. Exposure factors impact the "initial pool" of infections; hence they are contained in the $N(0)$ term. Consequently, we may express $N(0)$ as follows:

(3) $N(0) = f(X)$

where X is a set of exposure factors.

[5] This formula follows directly from equation (1) in Chowell et al. (2017) assuming early exponential growth. As Allain (2020) states, "…this model is pretty accurate for the early stages of an epidemic"

Environmental factors impact the infection and death rates; hence they are contained in the a and k terms. Consequently, we may express a and k as follows:

(4) $a = g(Z)$

(5) $k = h(Z)$

where Z is a set of environmental factors.

3. Data

There are two widely-used datasets with information on international air travel: (1) the Bureau of Transportation Statistics (BTS) International Origin and Destination (O&D) dataset and (2) the International T-100 dataset. The BTS International O&D is a quarterly, itinerary-level dataset, comprising a 10% sample of passenger itineraries that either include a flight into the US from abroad or that include a flight out of the US[6]. Each observation includes the originating airport for the trip, the final destination, as well as any airports where passengers stop or change planes. It only includes itineraries where at least one leg of the trip is operated by a US carrier. For those itineraries, it includes data for the entire itinerary, regardless of whether international carriers also operate some of the flights on the itinerary. The International T-100 dataset measures passenger volume on international flights at the carrier-route-month level. Each observation provides information on passenger volume on an airline between airports on international flights (one domestic airport and one international airport), however it does not include itinerary information about where passengers begin and end trips. Therefore, using the International T-100 data we cannot distinguish between incoming passengers that fly to JFK and end their trip, versus those that continue on to another US city. Similarly, we cannot distinguish passengers that begin their trip in Beijing versus those that fly to Beijing from another location before continuing on to JFK.

Recognizing the shortcomings of each dataset, we purchased the O&D International dataset from Airline Data for our main analysis. This dataset combines the

[6] We are unaware of prior use of these data for analyzing virus spread. Prior analyses of international airline travel vis a vis the U.S. has typically focused on competitive effects from international airline cooperation (e.g., Calzaretta et al., 2017; Lederman, 2007), along with several papers assessing the impact of 9/11 (e.g., Ito & Lee, 2005).

best features of the BTS International O&D and InternationalT-100 datasets. Specifically, the proprietary O&D International dataset uses the itinerary data from the BTS International O&D dataset, but with two enhancements. First, it uses data on travel flows from the International T-100 in order to scale the 10% sample up to approximate the full sample of itineraries.[7] In addition, the proprietary O&D International dataset includes information on itineraries into and out of the US that do not include any US carriers. Using the proprietary O&D International data, we sum the arriving international passengers at each US airport by the country where the trip originated, and then we sum these values across airports within the same MSA. For example, we sum up all the passengers whose trips begin in Italy and whose final destination in the US is JFK, LaGuardia (LGA), and Newark, because all three airports are in the New York City MSA. We do the same thing for trips originating from each country, and for each MSA within the US. This yields a dataset of passenger counts from each country to each MSA in the US. We then allocate the passengers for each MSA to the counties within that MSA according to the county's population share[8]. For example, in the Chicago MSA, Cook County represents 55% of the total population in the MSA while Newton County (IN) only represents about 0.1% of the MSA population. Therefore, we assign 55% of the total number of passengers arriving from Italy into the Chicago MSA to Cook County, while we only assign 0.1% of the passengers arriving from Italy into the MSA to Newton County.

Next, we merge the county-level passenger data with county-level data on COVID-19 cases and deaths from the New York Times. In addition, we merge in county-level data on population, population density, and various demographic characteristics.

Finally, we restrict our sample to counties in MSAs with an airport that received at least one arriving international passenger during the fourth quarter of 2019 (prior to the

[7] The process for integrating information from the T-100 data to scale up the O&D International data set is a proprietary one, developed by Airline Data Products, which is not available to us.

[8] We acknowledge that our approach for assigning passengers to counties based on population share is not perfect. Nonetheless, we think it is substantially more plausible than, e.g., assuming that passengers are uniformly distributed across counties within an MSA. This latter approach would make the very unrealistic assumption that the same number of passengers would be traveling to tiny Newton County, Indiana as to Cook County, Illinois.

onset of the pandemic in the US).[9] In total, our dataset comprises 987 counties in 289 MSAs.

Table 1 reports descriptive statistics for our sample. Specifically, we present the 10^{th}, 50^{th} (median), and 90^{th} percentiles for our variables within the samples we study. We see significant variation in outcomes, and in both our exposure and environmental variables.

[Table 1 about here]

4. Empirical Model

Our empirical strategy is straightforward: Examine whether counties in MSAs with more arriving international travelers experienced higher COVID-19 infection and death rates than counties in MSAs with fewer arriving international passengers. To do so, we begin with our simple theoretical model of infections:

$$(1)\quad N(t) = N(0) * (1 + a)^t$$

where: *N(t)* is the total number of infections in the region as of time *t*; *N(0)* is the total number of infections in the regions at some initial time, $t = 0$; and a is the infection rate.

Building on this model, COVID-19 cases (and deaths) in a county should be influenced by prior exposure, as well as environmental factors. Exposure influences the number of infections at time 0, while environmental factors influence how the number of infections grows over time.

We let $N(0) = f(X)$, where X is a set of exposure factors. Similarly, we let $a = g(Z)$, where Z is a set of environmental factors. Next, we consider a simple two-period model. In period 0, a location is exposed to the virus through some exogenous factor(s), X, which determine exposure, yielding N(0) infections. In period 1, the virus spreads. The extent of transmission, a, depends on the environmental factors, Z.

[9] This includes passengers whose trip originated outside of the US, but then took a connecting flight upon arrival in the US.

The following equation is the baseline version of our empirical model:

$$(6) \quad Log(N_{1cm})=a+X_{0cm}B + Z_{1cm}W+ e_{1cm}$$

In our model, $log(N_{1cm})$ measures the log number of infections (deaths) in county c, within metropolitan area m as of May 31, 2020. The exposure factors (X) consist of international air travelers from countries where the coronavirus was prevalent arriving at airports in metropolitan area m during period zero. We focus on passengers arriving from two countries, China and Italy, which, along with Iran[10], were the primary coronavirus hotspots during the onset of the pandemic. Specifically, X_{0cm} measures the number of international airline passengers arriving in county c of metro area m, during the fourth quarter of 2019.

The environmental factors (Z) consist of county population and population density, as well as county demographic characteristics including percent 65 and over, percent female, percent black, percent Hispanic, and percent Asian. In addition, confirmed infections are very strongly dependent on the amount of testing done. For this reason, we also control for cumulative tests conducted at the state level (we could not find testing data at the county level) on May 31, 2020. Finally, because the number of passengers arriving to each county within an MSA depends on the total number of passengers arriving to the MSA, we cluster our standard errors by MSA.[11]

Several features of our model are informed by the particulars of this pandemic. First, we focus our analysis on the early period of the pandemic (up to May 31) because we expect that after initial exposure, the subsequent spread of the virus should depend more on local environmental factors, especially given that the exposure from international passengers is (almost completely) shut off by mid-March for European travelers (start of February for travelers from China).

Next, because it is not clear when the coronavirus first began circulating in China or Italy, it is not clear which international passenger arrivals best capture initial US

[10] We do not focus on passengers arriving from Iran because of the small number of such passengers.
[11] Because we only observe passenger arrivals at the MSA level, we also estimate our model at the MSA level. We discuss the advantages and disadvantages of this approach below.

exposure to the coronavirus: international arrivals during the first quarter of 2020 or the fourth quarter of 2019. On the one hand, measuring arrivals during the first quarter of 2020 provides certainty that the coronavirus was circulating in both China and Italy. The first confirmed case in China was reported on December 31, 2019. Similarly, Italy reported its first COVID-19 cases on January 31, 2020. On the other hand, numerous reports have suggested that the coronavirus was circulating in both China and Italy during Q4 2019, and perhaps earlier (Vagnoni, 2020). Moreover, measuring arrivals during the fourth quarter of 2020 ensures that exposure precedes the cases and deaths that we observe. Further, measuring Q4 arrivals provides us with a complete quarter's worth of arrivals, unaffected by the bans on international travel into the US from China and Europe imposed at the end of January and in March. In addition, Q4 arrivals should be unaffected by heterogeneity in the severity of the pandemic across locations in the US because there were not yet any known cases of COVID-19 in the US. Finally, if the virus was not already present in Italy and/or China during the fourth quarter of 2019, then measuring exposure with fourth quarter passengers would reduce the likelihood of estimating a positive coefficient. Therefore, we conclude that using fourth-quarter passengers is a more conservative approach.[12]

In this model, B captures the effect of an increase in arriving international passengers in an MSA on the number of subsequent infections (deaths) in each county within that MSA. Because the dependent variable is in log form, $\Delta = 100 \times [\exp(B) - 1]$ represents the percent change in cases or deaths (depending on the model), resulting from an additional arriving passenger.

There are two important concerns with our ability to identify the causal effect of exposure from arriving passengers on COVID-19 infections and deaths (B). The first is that incoming passenger flows are likely endogenous to the spread of the virus. The number of foreign travelers to a metro area in the US will likely be influenced by the number of confirmed cases and deaths in that metro area. The second concern is that

[12] We also recognize that passenger flows are correlated over time. Therefore, fourth quarter passengers may proxy for first quarter passengers in our model. To the extent that the first-quarter measure is exogenous and precedes the spread of the disease in the US, this correlation would not be problematic for us, as we are interested in identifying the impact of first exposure, whenever it occurred. We discuss this further, below.

there may be unobservable characteristics of a metro area that are correlated with both COVID-19 cases (deaths) and international tourism. For example, it may be that, after controlling for, e.g., density, cities with newer developments are both more attractive to international travelers and less conducive to COVID-19 (e.g., because of newer buildings with better circulation). The first issue would unequivocally negatively bias our estimate of B; the latter issue may positively or negatively bias our estimate of B, depending on the signs of the relevant correlations (negative bias in our example).

As noted above, by focusing on travel during the fourth quarter of 2019, we are able to partially mitigate concerns that international travel to the US was influenced by the spread of the disease in the US. However, because passenger flows are correlated over time, it is likely that our estimate of B using passengers in Q4 2019 will capture some of the effects for passengers in Q1 2020, and is therefore subject to at least some of the same concerns about endogeneity.

To further address both of these issues, we use several different approaches. First, we use passengers arriving from non-COVID-19 hotspots to control for unobserved variation in local conditions. Specifically, we include passengers from three regions: Central and South America, Africa, and the Middle East (excluding Iran). Given the relatively lower number of confirmed cases in these regions during the first quarter of 2020, we expect that passengers from these regions were much less likely to be infected with the virus during fourth quarter of 2019 compared to passengers from China or Italy. Hence, this variable is well suited to serve as a proxy variable for unobservables that impact the spread of COVID-19 and are also correlated with international travel, at least from the aforementioned regions. To the extent that these passengers do effectively proxy for the aforementioned unobservables, this would leave unobservables that are correlated with Italian and/or Chinese passengers but are not correlated with passengers from these other regions as a potential source of bias. We believe that such idiosyncratic unobservables are unlikely to substantially bias our results.

Second, to address the concern that the virus was not yet widely prevalent in China or Italy during the Q4 2019, we examine the impact of passengers arriving during Q1 2020. Moreover, to address the concern that Q4 2019 passenger flows are correlated with Q1 2020 passenger flows, we also estimate models including passengers arriving during both quarters. This allows us to separately identify the effect of passengers arriving in each quarter.

Additionally, one might also be concerned about unobserved local characteristics that might impact virus spread and that are differentially correlated with arriving passengers. To address this, we also consider a model in which we include MSA fixed effects. In this model, we are correlating variation in arriving passengers across the counties within an MSA, with the spread of cases and deaths across the counties within each metro area. The MSA fixed effects control for unobserved characteristics that are correlated with both COVID-19 cases (deaths) and international tourism. For example, one might be concerned that passengers from China were disproportionately likely to travel to the West Coast, where there was very little spread of the virus during Spring 2020, while passengers from Italy were much more likely to travel to the Northeast, where the virus was most prevalent. The fixed effects would control for these differences across locations. The identification would come from variation in passengers and COVID-19 outcomes across each MSA's counties.

Finally, we also estimate an instrumental-variables model, in which we instrument for Q4 2019 and Q1 2020 arriving passengers with passengers arriving one year earlier. Because of the seasonality in travel patterns, passengers arriving one year earlier are highly correlated with passengers arriving during the start of the pandemic (we report the first-stage results in the Appendix). However, the passengers arriving one year earlier were not carrying the virus and therefore should be otherwise uncorrelated with the spread of COVID-19 in the US.

5. Results

Main Findings

Before examining the effects of passengers from China and Italy, we first look at total international passengers arriving from all countries, using the total number of arriving international passengers from around the world, regardless of where the trip originated, during the fourth quarter of 2019. Panel A reports results for cases through May 31, while Panel B reports results for deaths through May 31. The results in Column 1 indicate that counties with more international passengers arriving during the fourth quarter of 2019 do not experience a greater number of additional COVID-19 cases or deaths. This is expected, as the vast majority of these passenger arrived from non-COVID-19 hotspots.

[Table 2 about here]

In an effort to better isolate the causal effect of international travel on the spread of COVID-19 in the US, columns 2 and 3 report the results for travelers arriving from the two initial COVID-19 hotspots, China and Italy, during the fourth quarter of 2019. The results in Column 2 are surprising: passengers arriving from China reduce the spread of COVID-19 cases and deaths. Specifically, the results indicate that an additional 100 passengers arriving from China decreases the number of cases (deaths) by 0.86% (0.80%). The results in Column 3 fail to provide evidence that passengers from Italy affect the spread of the virus.

Taken together, the results in Columns 1-3 fail to provide any evidence of a positive correlation between international passenger arrivals and downstream COVID-19 cases and deaths. However, this could reflect unobserved local characteristics. For example, perhaps counties with more international business and tourism imposed more stringent policies more quickly to slow the spread of COVID-19 outbreaks.

To control for unobserved local characteristics related to international travel, in columns 4 and 5 we include the number of international passengers arriving from non-COVID-19 hotspots: Central and South America, Africa, and the Middle East. Doing so has little impact on the effect of travel from China. However, when we control for passengers from non-COVID-19 hotspots, the effect of passengers from Italy becomes much larger and statistically significant. These results suggest that passengers arriving from Italy increased the spread of COVID-19 cases and deaths. In addition, they suggest our control for other international passengers is picking up unobservables that are detrimental to COVID-19 spread but positively related to international travel in general (and travel from Italy in particular), as in our example from Section 4[13]. By including

[13] They also suggest that passengers from China are less strongly correlated with passengers from non-COVID-19 hotspots than are passengers from Italy (after partialing out the other variables in our model).

this control, endogeneity concerns are largely relegated to unobservables that impact COVID-19 spread and are correlated specifically with Italian passengers, beyond just a correlation with international travel in general. Quantitatively, the results in Column 5 indicate that an additional 100 passengers arriving from Italy increases county-level COVID-19 cases (deaths) during Q1 2020 by about 3.4% (3.9%).

Finally, to ensure that our results are not being driven by a correlation between travelers from China and travelers from Italy, in Column 6 we estimate the model with passengers arriving from both China and Italy, as well as passengers arriving from non-COVID-19 hotspots. Including travelers from China inflates the estimated effect of travelers from Italy, suggesting that the two sets of passenger arrivals are positively correlated. When we include travelers from China, the results in Column 6 indicate that an additional 100 passengers from Italy increases cases (deaths) by 4.6% (5.0%), while an additional 100 passengers from China reduces cases (deaths), but only by about one percent. The mean number of cases (deaths) in our sample is about 1,547 (120), indicating that, on average, an additional 100 arrivals from Italy in a county results in an additional 71 cases and about six additional deaths.

As discussed above, one might suspect that the coefficient on fourth quarter arrivals may be proxying for the effect of Q1 2020 arrivals. Because our focus is on assessing whether passengers from China and Italy exposed people in the US to the coronavirus, it is not crucial for our arguments whether this exposure actually occurred during the fourth quarter of 2019 or the first quarter of 2020. However, the magnitudes of our estimated effects in Table 2 will be positively biased (in absolute value) if the Q4 2019 coefficients are picking up some of the effect from Q1 2020 passengers. To assess this possibility, in Table 3 we examine the effect of passengers arriving during the first quarter of 2020.

[Table 3 about here]

Compared to the estimates for Q4 2019 passengers, the estimated marginal effects for Q1 2020 passengers are much larger and noisier. In the full model, the marginal effects of Q1 2020 passengers from Italy and China are about 4-8 times larger than the comparable effects for Q4 2019 passengers, while the standard errors are even more inflated. The larger effects for Q1 2020 passengers provide support for the claim that the estimates in Table 2 may be biased upward due to the serial correlation in passenger volumes. However, the very large standard errors highlight the uncertainty associated with these estimates, due to dramatically smaller passenger counts driven by the travel restrictions implemented during this time and the spreading pandemic. To try to separately identify the effects of Q4 versus Q1 passengers, in Table 4 we re-estimate the full model, including both Q4 2019 and Q1 2020 passengers.

[Table 4 about here]

The results in the first column of Table 4 indicate that when we include passengers arriving during the first quarter of 2020, our estimates for the fourth quarter of 2019 are very similar to those in Table 2. In contrast, the estimates for Q1 2020 switch signs, and are very noisy. We note that the Q1 2020 results do not imply Q1 passengers had no impact (the effects we estimate for Q4 2019 are well within any reasonable confidence interval for the Q1 2020 effects, including Italy); rather, the large standard errors strongly suggest challenges to precision due to travel disruptions during that time and strong correlation between Q4 2019 and Q1 2020 passengers[14]. Overall, these results provide little evidence that our Q4 2019 estimates in Table 2 are biased by the correlation in passenger flows over time. Nonetheless, to try and mitigate the noisiness of the Q1 2020 estimates, in Column 2 we sum the total number of passengers from each location across two quarters. The estimates are very similar to those for Q4 2019.

Taken together, the results in Tables 2-4 provide robust evidence that counties that received more passengers from Italy during the early period of the pandemic experienced greater caseloads and deaths, while providing no such evidence for counties receiving more passengers from China. Indeed, our results suggest that arrivals from China are associated with a smaller number of cases and deaths from Covid.

As noted in Section 4, there may be concerns about unobservable local characteristics influencing our results. Consequently, we re-estimate our baseline models

[14] Passengers from Italy arriving during Q4 and Q1 are extremely highly correlated (r =0.96).

including MSA fixed effects. The MSA fixed effects allow us to rule out the possibility that our results are driven by time-invariant unobservables that are correlated with passengers from Italy and China. In these models, we identify the effect on county-level COVID-19 outcomes exploiting only the variation in passengers across counties within the same MSA. However, because we only observe passenger arrivals at the MSA level, and we assign passengers to counties based on the county's population share, the within-MSA variation in passengers results only from variation in the population share of each county. In this case, we assume that the county's population share provides a proxy for the fraction of passengers arriving in the MSA that travel to each county within the MSA.[15] We report the results of this analysis in Table 5. For this and all subsequent analyses, we consider three specifications of the full model: (1) Q4 passengers only; (2) Q1 and Q4 passengers separately; (3) Q1 and Q4 passengers combined.

[Table 5 about here]

As we would expect, the estimates in Table 5 are much noisier. Nonetheless, the pattern of results is generally consistent with the baseline results above. Even after controlling for unobserved MSA characteristics, we find that passengers arriving from Italy during Q4 2019 increase the spread of Covid, while we find no evidence that passengers arriving from China do so. These results hold when we include Q1 passengers, and when we combine the Q4 and Q1 passengers.

To address any remaining concerns about the endogeneity of passenger arrivals, we instrument for arriving passengers during the early period of the pandemic with the number of passengers arriving one year earlier. For example, we instrument for passengers arriving from Italy during the fourth quarter of 2019 with passengers arriving from Italy during the fourth quarter of 2018. Because of the seasonality in travel patterns, passengers arriving one year earlier are highly correlated with passengers arriving during the start of the pandemic (we report the first-stage results in the Appendix). However, the passengers arriving one year earlier were not carrying the virus and therefore should be

[15] See Appendix for a more detailed discussion of identification in this model.

otherwise uncorrelated with the spread of COVID-19 in the US. We report the results of our IV analysis in Table 6.

[Table 6 about here]

Again, we find that passengers arriving from Italy during Q4 2019 increase the spread of Covid, while we find no evidence that passengers arriving from China do so. When we include passengers arriving during Q1 2020 (we instrument for them using passengers arriving during Q1 2019) we find no statistically significant effects, as the estimates become extremely noisy, but when we combine the arrivals from the two quarters (and instrument for them with the sum of arrivals from Q4 2018 and Q1 2020), the results are much more precise and very similar to those when we only include Q4 2019 passengers. In total, the pattern of results is very consistent with our earlier analyses, and consistent with the fixed-effects models, provides very little indication that endogeneity is driving our results.

Robustness Checks

In the Appendix, we present additional analyses that demonstrate the robustness and limitations of our findings. First, we run our full model on each of the individual datasets that were integrated and enhanced to produce the dataset we have used: the BTS O&D and T-100 datasets. Both datasets yield results consistent with our main findings.

Second, we note that there is no clear theoretical guidance concerning the functional form of the relationship between COVID-19 cases/deaths and arriving international passengers. To address this, we re-run our analyses using a cubic polynomial for each of our passenger measures. We find qualitatively similar results across all our models using the cubic functional forms, typically finding even larger magnitudes – negative for China and positive for Italy.

Lastly, we re-estimate our model at the MSA level (using our primary dataset, the proprietary O&D International dataset). The advantage of this approach is that it is consistent with the source of variation in the passenger arrivals; passengers arrive to MSAs, not to counties. In addition, this approach should better capture the full effect of arrivals on the spread of Covid, as it allows for arriving passengers to infect people in multiple counties within the same MSA, and it captures the effect of second-hand transmission, as arriving passengers infect people in County A, who then transmit the virus to people in other counties within the MSA. However, this approach ignores the substantial within-MSA variation in COVID-19 outcomes, population, and demographics across counties and relies on only cross-MSA variation in passengers, which is quite plausibly endogenous.[16] Moreover, with only 289 MSAs, identifying as many as 14 coefficients asks a lot of the data, raising concerns about the stability of the estimates.

The MSA-level results show negative impacts for all passenger types (Italian, Chinese, and other international passengers). We recognize this result may cast some doubt on our positive findings for Italian passengers. However, we believe it has two key implications. First, it again shows a lack of impact from Chinese passengers on U.S. COVID-19 outcomes, further demonstrating the robustness of this finding. Second, it demonstrates why MSA-level analysis on these data likely has important shortcomings. Namely, if one believes the results of the MSA-level analysis to be qualitatively correct, then it raises the question: what did spread the virus all over the US? One might argue that once the virus arrived in the US initially it was spread exclusively via community transmission. However, given that our results hold even for the very earliest phase of the pandemic, community transmission seems like a very unlikely explanation.[17]

Conclusions

Since the onset of the COVID-19 pandemic, policymakers, researchers, and others have argued about the factors that drive the spread of the virus. Particularly, during the early phase of the pandemic, the striking geographic heterogeneity of the spread of the virus raised a natural question: Why did New York City experience such a severe outbreak early on while Los Angeles emerged relatively unscathed?

[16] MSA-level unobservables, such as local news coverage of the virus and local reactions as a function of the prevalence of international travel to an MSA, may be particularly likely to be correlated with both international passenger volume and virus spread. Hence, a model relying only on cross-MSA variation may suffer from much greater endogeneity problems than one relying also, or only, on cross-county (within-MSA) variation.

[17] See Appendix for results through March 31.

Epidemiological models suggest possible answers to this question: Exposure and environmental factors. For any location, international travelers arriving from COVID-19 hotspots represent a source of exposure to the virus. In contrast, environmental factors including population size and density, use of public transportation, air pollution, demographics, local policies, local economic activity, affect the virus's spread and impact after it has arrived in a location (e.g., Adda 2016, Clay et al. 2019).

Using a model that accounts for key variables affecting exposure and environment, our analysis answers the following question: Did travelers from China and Italy How much of the variation spread the virus across the US during the early phase of the pandemic? We find two key results. Counties that received more passengers from China did not experience higher infection and fatality rates; in fact, both outcomes were lower. In contrast, counties that received more passengers from Italy experienced higher infection and fatality rates. Specifically, our estimates indicate that an additional 100 passengers from Italy arriving in a given county increased case (death) rates by about five percent.

Our findings are important in terms of looking back to understand the source of the epidemic in the US. They suggest that stopping travel from Europe earlier likely would have had greater impact on reducing the spread of the virus in the US, compared to the relatively early ban on travel from China. Nonetheless, perhaps more importantly, these results suggest that, in the event of future outbreaks (of this and other viruses), banning travel from virus hotspots may be smart policy, depending on the specific characteristics of the virus.

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Tables

Table 1: Descriptive Statistics

	Counties with At Least One Case	Counties with At Least One Death
	Median	Median
County-level cases through May 31	172	315
County-level deaths through May 31	5	12
Q4 IntlPassengers All Countries (00s)	1725	2611
Q4 IntlPassengers China (00s)	35	58
Q4 IntlPassengers Italy (00s)	36	62
Q4 IntlPassengers non-COVID Countries (00s)	723	1173
Tests through May 31 - State	338,127	375,109
County Demographics		
Population	82,126	129,866
Population Density	138	227
% 65 and older	0.168	0.162
% Female	0.506	0.507
% Black	0.056	0.074
% Hispanic	0.057	0.061
% Asian	0.014	0.017
N (counties)	987	770
MSAs	289	259

Table 2: The Effect of Q4 2019 International Passengers on County-Level Cases and Deaths Through May 2020

Panel A: Cases						
	Ln(Cases)	Ln(Cases)	Ln(Cases)	Ln(Cases)	Ln(Cases)	Ln(Cases)
Q4 IntlPassengers All Countries (00s)	-0.0003 (0.0002)					
Q4 IntlPassengers China (00s)		-0.0086*** (0.0015)		-0.0085*** (0.0014)		-0.0103*** (0.0014)
Q4 IntlPassengers Italy (00s)			0.0107 (0.0109)		0.0334*** (0.0087)	0.0449*** (0.0046)
Q4 IntlPassengers non-COVID Countries (00s)				-0.0000 (0.0002)	-0.012** (0.0004)	-0.0014*** (0.0002)
County Population (000s)	0.0017*** (0.0004)	0.0020*** (0.0003)	0.0010*** (0.0000)	0.0020*** (0.0003)	0.0012*** (0.0004)	0.0021*** (0.0003)
Population Density(00s)	0.0084*** (0.0026)	0.0075*** (0.0020)	0.0053*** (0.0046)	0.0076*** (0.0021)	0.0020 (0.0040)	0.0002 (0.0024)
% 65 and older	-14.09*** (1.81)	-13.98*** (1.78)	-15.36*** (1.93)	-13.96*** (1.79)	-15.16*** (1.90)	-14.20*** (1.82)
% Female	21.62*** (4.92)	20.12*** (4.72)	22.90*** (4.99)	20.11*** (4.74)	22.52*** (4.89)	19.49*** (4.54)
% Black	2.68*** (0.45)	2.50*** (0.42)	2.66*** (0.45)	2.51*** (0.42)	2.74*** (0.45)	2.54*** (0.42)
% Hispanic	0.89 (0.58)	0.43 (0.53)	0.83 (0.57)	0.44 (0.53)	1.03 (0.57)	0.52 (0.52)
% Asian	8.62*** (2.24)	8.68*** (1.98)	7.95*** (2.24)	8.66*** (2.02)	7.31*** (2.03)	8.09*** (1.62)
Tests_State (000s)	0.0253 (0.0203)	0.0253 (0.0203)	0.0223 (0.0151)	0.0283 (0.0196)	0.0168 (0.0136)	0.0172 (0.0136)
N (Counties)	987	987	987	987	987	987
MSAs	289	289	289	289	289	289
Panel B: Deaths						
	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)
Q4 IntlPassengers All Countries (00s)	-0.0003 (0.0002)					
Q4 IntlPassengers China (00s)		-0.0080*** (0.0015)		-0.0080*** (0.0014)		-0.0100*** (0.0013)
Q4 IntlPassengers Italy (00s)			0.0142 (0.0114)		0.0379*** (0.0083)	0.0490*** (0.0042)
Q4 IntlPassengers non-COVID Countries (00s)				0.0000 (0.0002)	-0.0012*** (0.0004)	-0.0014*** (0.0002)
County Population (000s)	0.0016*** (0.0004)	0.0019*** (0.0003)	0.0009** (0.0004)	0.0019*** (0.0003)	0.0012*** (0.0004)	0.0020*** (0.0003)
Population Density	0.0102*** (0.0029)	0.0095*** (0.0023)	0.0066 (0.0049)	0.0094*** (0.0024)	0.0031 (0.0042)	0.0009 (0.0027)
% 65 and older	-2.47 (1.88)	-2.34 (1.88)	-4.10** (2.05)	-2.38** (1.88)	-3.90* (2.01)	-2.86 (1.88)
% Female	23.39*** (6.46)	21.53*** (6.13)	24.75*** (6.55)	21.55*** (6.15)	24.23*** (6.41)	20.58*** (5.82)
% Black	1.50***	1.34**	1.42**	1.34**	1.52***	1.38***

	(0.55)	(0.54)	(0.54)	(0.53)	(0.55)	(0.52)
% Hispanic	0.33 (0.53)	-0.18 (0.49)	0.22 (0.52)	-0.19 (0.47)	0.48 (0.52)	-0.10 (0.46)
% Asian	8.16*** (2.53)	8.39*** (2.29)	7.43*** (2.64)	8.42*** (2.34)	6.74*** (2.36)	7.77*** (1.66)
Tests_State (000s)	0.00001 (0.0002)	0.00001 (0.0002)	0.00001 (0.0002)	0.00001 (0.0002)	-0.0000 (0.0001)	0.0000 (0.0001)
N (Counties)	770	770	770	770	770	770
MSAs	259	259	259	259	259	259

*p-value<.10; **p-value<.05; ***p-value<.01.
We cluster standard errors by MSA. Sample includes counties in MSAs with at least one arriving international passenger during Q4 2019.

Table 3: The Effect of Q1 2020 International Passengers on County-Level Cases and Deaths Through May 2020

Panel A: Cases			
	Ln(Cases)	Ln(Cases)	Ln(Cases)
Q1 IntlPassengers China (00s)	-0.062*** (0.016)		-0.078*** (0.017)
Q1 IntlPassengers Italy (00s)		0.035 (0.128)	0.163** (0.082)
Q1 IntlPassengers non-COVID Countries (00s)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)
N (Counties)	987	987	987
MSAs	289	289	289
Panel B: Deaths			
	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)
Q1 IntlPassengers China (00s)	-0.055*** (0.015)		-0.073*** (0.016)
Q1 IntlPassengers Italy (00s)		0.064 (0.128)	0.183** (0.087)
Q1 IntlPassengers non-COVID Countries (00s)	0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)
N (Counties)	770	770	770
MSAs	259	259	259

*p-value<.10; **p-value<.05; ***p-value<.01.
We cluster standard errors by MSA. Sample includes counties in MSAs with at least one arriving international passenger during Q4 2019.

Table 4: The Effect of Q4 2019 and Q1 2020 International Passengers on County-Level Cases and Deaths Through May 2020

Panel A: Cases		
	Ln(Cases)	Ln(Cases)
Q4 IntlPassengers China (00s)	-0.010** (0.005)	
Q4 IntlPassengers Italy (00s)	0.054*** (0.017)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.002*** (0.001)	
Q1 IntlPassengers China (00s)	0.012 (0.030)	
Q1 IntlPassengers Italy (00s)	-0.092 (0.097)	
Q1 IntlPassengers non-COVID Countries (00s)	0.002 (0.002)	
(Q4 and Q1) IntlPassengers China (00s)		-0.010*** (0.001)
(Q4 and Q1) IntlPassengers Italy (00s)		0.039*** (0.004)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)		-0.001*** (0.000)
N (Counties)	987	987
MSAs	289	289
Panel B: Deaths		
	Ln(Deaths)	Ln(Deaths)
Q4 IntlPassengers China (00s)	-0.011** (0.005)	
Q4 IntlPassengers Italy (00s)	0.058*** (0.016)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.002*** (0.001)	
Q1 IntlPassengers China (00s)	0.027 (0.031)	
Q1 IntlPassengers Italy (00s)	-0.092 (0.097)	
Q1 IntlPassengers non-COVID Countries (00s)	0.002 (0.001)	
(Q4 and Q1) IntlPassengers China (00s)		-0.010** (0.001)
(Q4 and Q1) IntlPassengers Italy (00s)		0.043*** (0.004)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)		-0.001*** (0.000)
N (Counties)	770	770
MSAs	259	259

*p-value<.10; **p-value<.05; ***p-value<.01.
We cluster standard errors by MSA. Sample includes counties in MSAs with at least one arriving international passenger during Q4 2019.

Table 5: The Effect of Q4 2019 and Q1 2020 International Passengers on County-Level Cases and Deaths Through May 2020, with MSA Fixed Effects

Panel A: Cases			
	Ln(Cases)	Ln(Cases)	Ln(Cases)
Q4 IntlPassengers China (00s)	-0.008*** (0.002)	-0.000 (0.006)	
Q4 IntlPassengers Italy (00s)	0.022*** (0.007)	0.023 (0.018)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.002*** (0.001)	-0.003** (0.001)	
Q1 IntlPassengers China (00s)		-0.058* (0.035)	
Q1 IntlPassengers Italy (00s)		-0.014 (0.095)	
Q1 IntlPassengers non-COVID Countries (00s)		-0.001 (0.002)	
(Q4 and Q1) IntlPassengers China (00s)			-0.008*** (0.002)
(Q4 and Q1) IntlPassengers Italy (00s)			0.021*** (0.007)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)			-0.001** (0.001)
N (Counties)	987	987	987
MSAs	289	289	289
Panel B: Deaths			
	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)
Q4 IntlPassengers China (00s)	-0.007*** (0.002)	-0.003 (0.007)	
Q4 IntlPassengers Italy (00s)	0.023*** (0.008)	0.028 (0.022)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.002*** (0.001)	-0.003 (0.002)	
Q1 IntlPassengers China (00s)		-0.021 (0.040)	
Q1 IntlPassengers Italy (00s)		-0.053 (0.124)	
Q1 IntlPassengers non-COVID Countries (00s)		0.001 (0.003)	
(Q4 and Q1) IntlPassengers China (00s)			-0.007*** (0.002)
(Q4 and Q1) IntlPassengers Italy (00s)			0.021*** (0.007)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)			-0.001** (0.000)
N (Counties)	770	770	770
MSAs	259	259	259

*p-value<.10; **p-value<.05; ***p-value<.01.
We cluster standard errors by MSA. All models include MSA fixed effects. Sample includes counties in MSAs with at least one arriving international passenger during Q4 2019.

Table 6: The Effect of Q4 2019 and Q1 2020 International Passengers on County-Level Cases and Deaths Through May 2020, Instrumental Variables Analysis

Panel A: Cases			
	Ln(Cases)	Ln(Cases)	Ln(Cases)
Q4 IntlPassengers China (00s)	-0.011*** (0.001)	-0.004 (0.017)	
Q4 IntlPassengers Italy (00s)	0.042*** (0.005)	0.031 (0.052)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.001*** (0.000)	-0.003*** (0.001)	
Q1 IntlPassengers China (00s)		-0.016 (0.132)	
Q1 IntlPassengers Italy (00s)		0.013 (0.403)	
Q1 IntlPassengers non-COVID Countries (00s)		0.004 (0.002)	
(Q4 and Q1) IntlPassengers China (00s)			-0.010*** (0.001
(Q4 and Q1) IntlPassengers Italy (00s)			0.037*** (0.004)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)			-0.001*** (0.000)
N (Counties)	987	987	987
MSAs	289	289	289
Panel B: Deaths			
	Ln(Deaths)	Ln(Deaths)	Ln(Deaths)
Q4 IntlPassengers China (00s)	-0.010*** (0.001)	-0.001 (0.025)	
Q4 IntlPassengers Italy (00s)	0.047*** (0.004)	0.080 (0.066)	
Q4 IntlPassengers non-COVID Countries (00s)	-0.001*** (0.000)	-0.003*** (0.001)	
Q1 IntlPassengers China (00s)		-0.051 (0.200)	
Q1 IntlPassengers Italy (00s)		-0.305 (0.514)	
Q1 IntlPassengers non-COVID Countries (00s)		0.003 (0.003)	
(Q4 and Q1) IntlPassengers China (00s)			-0.009*** (0.001
(Q4 and Q1) IntlPassengers Italy (00s)			0.037*** (0.004)
(Q4 and Q1) IntlPassengers non-COVID Countries (00s)			-0.001*** (0.000)
N (Counties)	770	770	770
MSAs	259	259	259

*p-value<.10; **p-value<.05; ***p-value<.01.

We cluster standard errors by MSA. Sample includes counties in MSAs with at least one arriving international passenger during Q4 2019.