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Short Communication

The effects of different travel modes and travel destinations on COVID-19 transmission in global cities

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The international community has made significant efforts to flatten the COVID-19 curve, including predicting transmission [1, 2], executing unprecedented global lockdowns and social distancing [3, 4], promoting the wearing of facemasks and social distancing measures [5], and isolating confirmed cases and contacts [6]. Because of the adverse consequences of these lockdown measures [7], many cities have reopened so they can rebuild their economies. However, as mobility has gradually towards normal, imported cases from unknown sources have disrupted the recovery situation, and cities are continually at high risk of new waves of infection [8, 9] since airborne transmission is the dominant transmission route [10]. Unlike study focusing on the effect of COVID-19 on changes in mobility [11], our study aims to determine the causative relationship and quantify the effects between travel modes and travel destinations and transmission of the pandemic, which is helpful to control the pandemic, especially during the reopening period as mobility progressively returns to normal.

By specifically focusing on urban mobility, one epidemiological study suggested that the transmission risk associated with public transportation, such as in trains with confined spaces, can lead to changes based on travel time and seat location, with the highest risk being found among passengers adjacent to an infected patient [12]. However, it remains unclear how different travel modes and activities at travel destinations affect the transmission of COVID-19, and understanding this relationship is crucial for people with frequent commutes as part of their daily lives. It is because airborne transmission is the dominant transmission method for COVID-19 that they can be infected with a much higher probability [10]. Without rigorous study, the population at large may consider that travel modes and activities at travel destinations they newly adopted have a relatively lower risk. This perception may create a relatively safe situation during a certain period while it may also lead to new waves of the pandemic when there is a structural change of travel modes (e.g., major commuting shifting from subways to walking) or there are new infection groups associated with specific activities. In addition, riskier travel modes may be different between cities, and people having no such awareness may end up using the riskier modes [13], which is also influenced by public health interventions (i.e., increasing awareness, disinfection, and stay-at-home policy) that can help control the spread of disease [14]. Thus, it is crucial to quantify these effects on daily confirmed cases at a global scale to inform policy making and to provide useful guidance regarding safe forms of transit for the general public.

The correlations of population density (Fig. S1 online) and facemask wearing (Fig. S2 online) to daily infections are discussed in the Supplementary materials (SM). To determine the causative relationship and quantify the travel mode effect, this study developed a vector autoregression model (VAR) by incorporating a time series of daily confirmed cases (*c*) using the daily proportions of those individuals driving (*d*), using public transit (*t*), and walking (*w*) and applying the model to each of the 58 cities in 31 countries (Fig. 1a) from February 15, 2020 to December 31, 2020. Similarly, to quantify the travel destination effect, we developed the same model to incorporate *c* with six types of travel destinations, i.e., retail and recreation (*rr*), groceries and pharmacies (*gp*), parks (*pk*), transit stations (*st*), workplaces (*wk*), and residences (*re*), applied to the same 58 cities and the same period. The travel mode data are the daily proportions of each travel mode relative to the number of the corresponding users on a referenced day in each city, the same for the travel destination data. The persistence calculated by the auto-correlation function is significantly greater than 0.2 for each of the four variables *c*, *d*, *t*, and *w* (Fig. S3 online). This means that they exhibit stable persistence in most cities and the daily confirmed cases, and the three travel modes create trend patterns in the series that can help establish a robust model to identify the causal relationship (see SM). Meanwhile, *rr*, *pk*, *st*, and *re* also obtain stable persistence in most cities, but *gp* and *wk* have relatively low persistence (Fig. S4 online), suggesting that the global pandemic and lockdown have disrupted the mobility trend for groceries and pharmacies and that for workplaces. In addition, none of the three travel modes or six travel destinations in any of the 58 cities show any structural break in the residuals, as none of the stability curves exceed the upper and lower confidence intervals, which demonstrates that the established models for each city are stable.

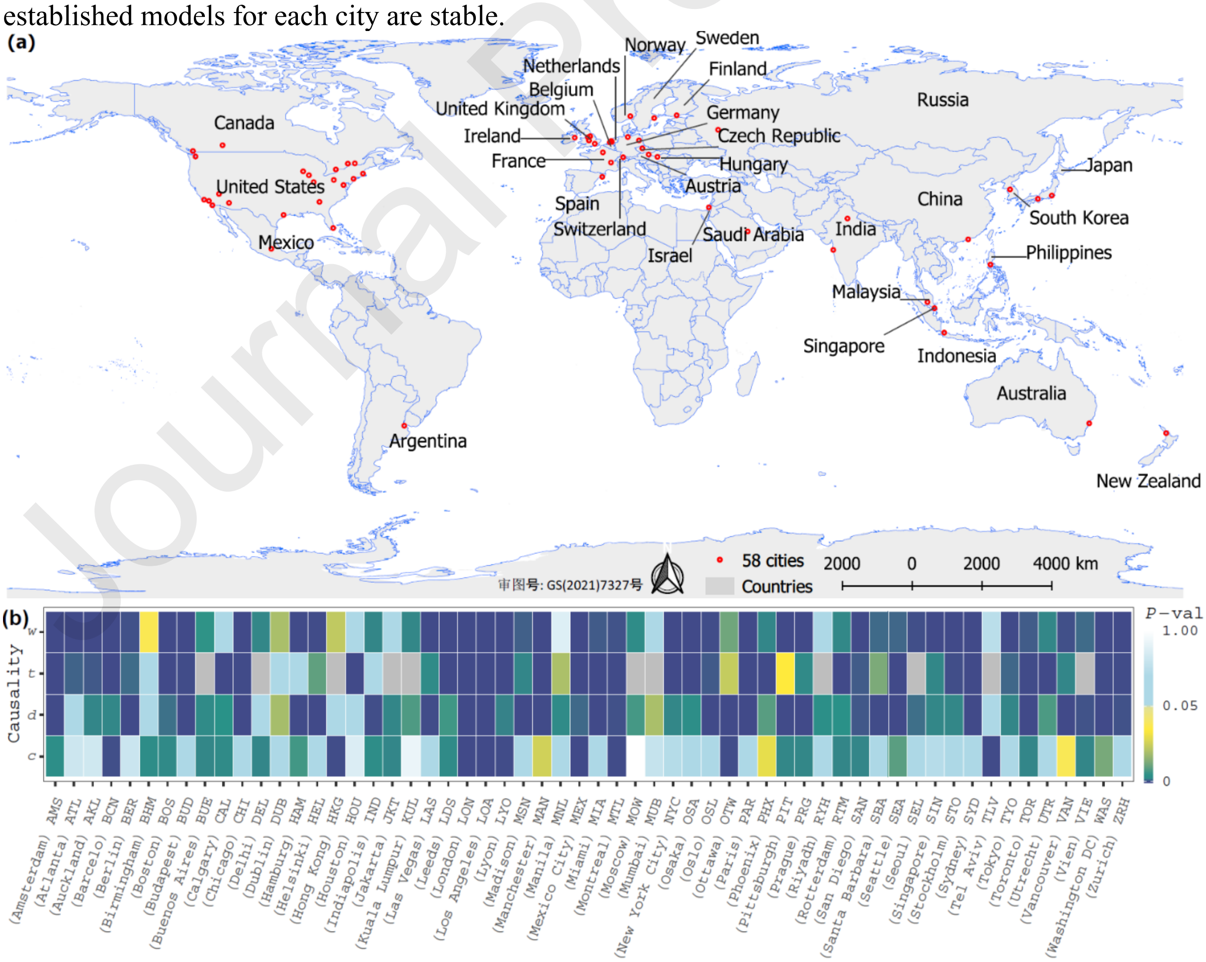

Fig. 1. The Granger-causality matrix between the four variables in worldwide cities. (a) The study investigates 58 cities in 31 countries across the continents of America, Asia, Europe, and Oceania. (b) One variable is the Granger-causality of the other three variables with the 95% CI. The grey tiles in public transit (*t*) are null due to missing information in the original data set.

The vast majority of the 58 cities revealed an optimal lag at seven days (note that for Riyadh, it was six days) based on four indicators—the Akaike information criterion, Hannan-Quinn criterion, Schwarz criterion, and the final prediction error; this is the same as the longest incubation period, i.e., 5.2 days, with a 95% confidence interval (CI) between 4.1 and 7.0 days [15]. As some people are asymptomatic carriers, this also indicates that they may continue the same travel behaviour during the incubation period until they test positive. Since urban mobility can spread the infection, and simultaneously, the pandemic can influence the rates of travel modes and travel destinations, a Granger-causality analysis is performed to determine the causality of one variable on the other variables (SM). It is found that *d*, *t*, and *w* cause the changes of the other three variables ($P<0.05$) in 89.7%, 91.5%, and 87.9% of the cities, respectively, and *c* Granger-causes the changes of travel modes in 51.7% of the cities (Fig. 1b). In comparison, *pk* (75.9%), *st* (86.2%), *wk* (91.4%), *rr* (96.6%), *gp* (96.6%), and *re* (100%) Granger-cause the other six variables, and daily confirmed cases cause a change in travel destinations in 83.1% of the cities (Fig. S5 online). The results suggest that travel modes and travel destinations can influence the cases in the vast majority of the cities. Since the effect of daily confirmed cases on travel modes and destinations is only in 51.7% and 83.1% of the cities respectively, it indicates that travel modes are more stable than travel destinations in face of the pandemic shock as they are less affected by daily confirmed cases.

Next, we calculate the changes in daily confirmed cases (Δc) caused by a positive shock (i.e., random variation within a standard deviation) to each of the three travel modes (Figs. S6-S8 online) and each of the six travel destinations (Figs. S9-S14 online) using the impulse response function (IRF) with 100 iterations and a 95% CI, which allows us to test the impacts of the travel modes and destinations on daily confirmed cases based on the mean and standard errors. Here, we only consider the variables in each city that have been determined to Granger-cause the other variables. Overall, driving, walking, and public transit can accelerate infection in 22 cities (42.3%), 30 cities (58.8%), and 38 cities (88.4%) (Fig. S15 online), respectively. The standard errors are significantly small in most cities, which suggests that the results exhibit high reliability. Notably, the IRF also obtains negative values for the three travel modes; however, this does not mean that travel modes in these cities can decelerate the infection. A reasonable explanation is that increasing the share for one mode (e.g., driving) may lead to a decrease in the number of cases, that is not because of some healthy impact of the act of driving but rather that an increase in the relative mode share for driving can represent a substitute for the share of another mode (e.g., public transit), which consequently mitigates pandemic transmission. In addition, travel destinations for those trips associated with specific activities also play an important role in changing the infection numbers. Travel destinations associated with parks (10 cities, 22.7%), groceries and pharmacies (17 cities, 30.4%), retail and recreation (26 cities, 26.4%), residences (29 cities, 50.9%), workplaces (33 cities, 62.3%), and transit stations (37 cities, 74.0%) have an increasing effect on the pandemic transmission at a global scale (Fig. S16 online).

Figs. S15 and S16 (online) reveal four critical findings. First, public transit causes more disease spread than driving or walking. It is assumed that passengers in public transit (e.g., buses and metros) are confined to small, enclosed spaces, which makes it challenging to maintain the one-meter-plus social distancing rule. Second, a positive shock to driving or walking may represent a substitute for another mode share and thus have a relatively "mitigation" effect on COVID-19 transmission in some cities, such as London, Chicago, Paris, and New York City. The other possible reasons are that people in these cities have a strong awareness of self-protection, policies in these cities restrict the number of people moving in public spaces, and disinfection activity is increased in these cities [14]. Third, all travel modes promote COVID-19 transmission in some cities (e.g., Budapest, Madison, Manchester, Miami, Osaka, Ottawa, and Pittsburgh) which suggests that urban mobility can represent a major transmission route in these cities. Fourth, the travel destinations of transit stations, workplaces, and residences are the three most influential factors in the spread of COVID-19, which indicates that lockdown measures with a work-from-home policy can be an effective way to control the pandemic transmission [14].

In the IRF, Δc which denotes the changes of daily confirmed cases has a different order of magnitudes in different cities. To make the changes comparable across all cities on the same scale between [0, 1], the variance decompositions (VDs) of daily confirmed cases, driving, public transit, and walking denoted by $\{v_c, v_d, v_t, v_w\}$ are computed for 100 iterations (runs) of the method (Figs. S17-S20 online) and the same computation is made for daily confirmed cases associated with the travel destinations and recorded by $\{v_c, v_{rr}, v_{gp}, v_{pk}, v_{st}, v_{wk}, v_{re}\}$ (Figs. S21-S27 online). Since $\{v_c\}$ decreases with an increase in runs (Figs. S17 and S21 online), the 25th percentile of v_c is summarized to investigate their stable impacts on c. The result shows that 69.0% versus 31.0% of the cities have v_c larger and smaller than 0.5, respectively when associating with the effects of travel modes (Fig. 2a), which means that the infectious source is more effective than travel modes in influencing coronavirus transmission and suggests that strictly controlling infectious sources should be considered an urgent measure. In addition, 44.8% versus 55.2% of the cities meet the same criteria when associating with the effects of travel destinations (Fig. S28 online), meaning that at a global scale, travel destinations tend to be the most important factor that contributes to the daily confirmed cases when compared with infectious sources. This indicates that strict social distancing should be implemented for activities at travel destinations. Moreover, the main contribution to infections in several cities is from both travel modes and travel destinations as v_c<0.5 in both cases, including Helsinki, Mexico City, Miami, Osaka, Phoenix, Prague, Utrecht, and Vancouver.

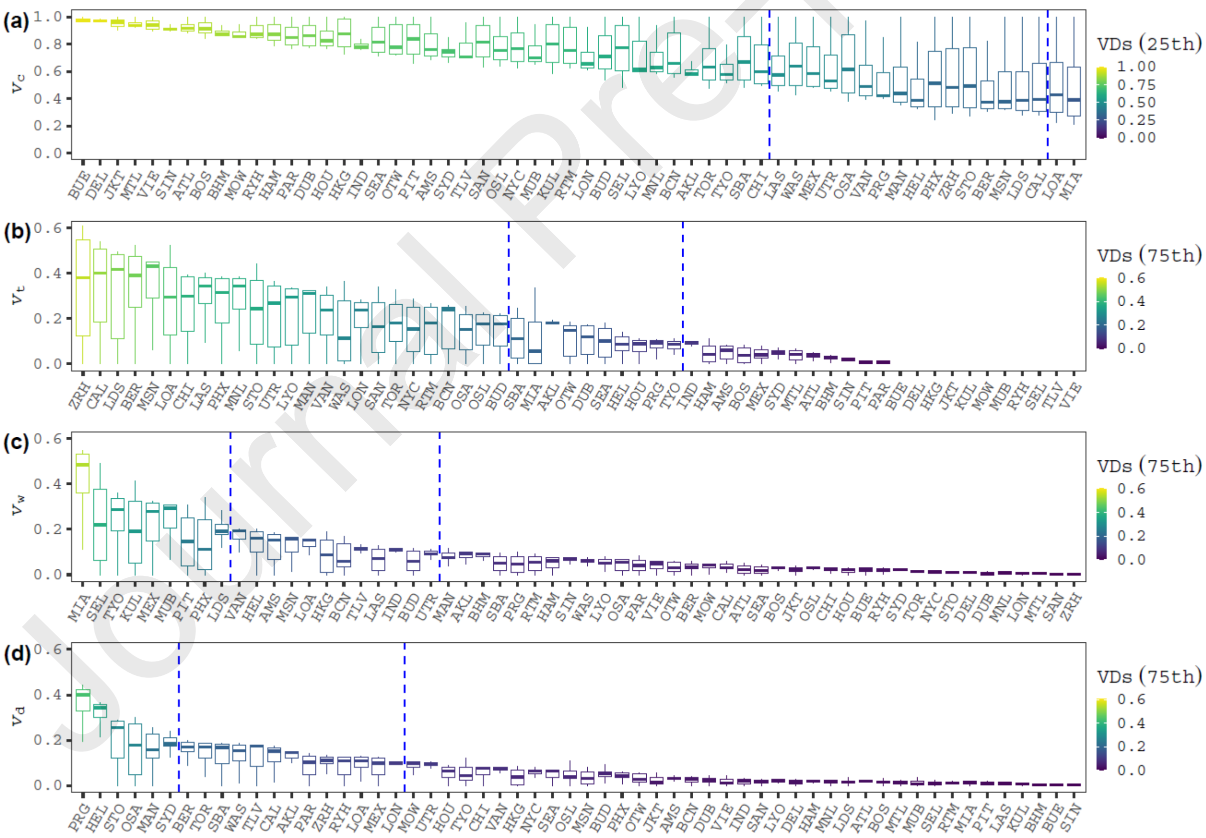

Fig. 2. Contribution of infectious sources and travel modes (variance decompositions, VDs) to daily confirmed cases. In the x-axis, the full city names can be referred to Fig. 1. (a) The blue dashed line divides the box plots when the 25th percentile of VDs is in [0, 0.25), [0.25, 0.5), and [0.5, 1]. There are 2 (3.4%), 16 (27.6%), and 40 (69.0%) cities in the three corresponding categories, respectively. (b–d) The blue dashed lines divide the box plots when the 75th percentile of VDs is in [0.2, 1], [0.1, 0.2), and [0, 0.1). (b) For public transit, 25 (43.1%), 10 (17.2%), and 23 (39.7%) cities. Notably, eleven cities are unavailable in the original data set. (c) For walking, 9 (15.5%), 12 (20.7%), and 37 (63.8%) cities. (d) For driving, 6 (10.3%), 13 (22.4%), and 39 (67.3%) cities.

The analysis of VD values of the travel modes and travel destinations also allows us to make a direct comparison of the impacts of urban mobility, which are organized by the 75th percentile of the three travel modes and six travel destinations. Overall, public transit exhibits the largest contribution to daily confirmed cases in 43.1% of the cities (Fig. 2b), followed by walking (15.5%, Fig. 2c) and driving (10.3%, Fig. 2d) when their $v \geq 0.2$. Fig. 2 displays four phenomena. First, driving is the safest travel mode given that, in general, v_d is smaller for driving than for the other two modes. A reasonable explanation is that drivers effectively separate themselves from strangers, thus minimizing their chance of being infected. Second, walking is a risky travel mode in many cities, which is likely beyond people's expectations. Third, unlike the previous notion that public transit, such as metros and buses, tend to spread the pandemic to a wider and deeper degree because of the ease of spread in small, enclosed spaces, the transmission via public transit is insignificant in a few cities, with $v_w<0.1$. Fourth, different cities behave differently with respect to the functionality of the different travel modes. For example, the six largest cities where walking has a major contribution to infections (i.e., Miami, Seoul, Tokyo, Kuala Lumpur, Mexico City, and Mumbai) are all worldwide megacities. Furthermore, the three Nordic cities (i.e., Stockholm, Oslo, and Helsinki) are significantly impacted by public transit.

In comparison, different travel destinations obtain a similar VD distribution wherein only a few cities (less than 17.2%) get $v \in [0.2, 0.6)$, while the majority of cities (56.9% to 77.6%) have $v \in [0, 0.1]$ (Fig. S29 online). Travelling for transit stations is the major transmission route in the three Nordic cities, which is consistent with the result obtained for travel modes. Even though Hong Kong and Singapore in Asia share many similarities, the pandemic in Hong Kong was mainly transmitted via travel for retail and recreational activities while in Singapore, it was mainly affected by the travel destination of parks and transit stations.

Our study is important in light of the widespread misconceptions about the effects of travel modes and travel destinations on COVID-19 transmission. First, travel destinations associated with various activities (i.e., transit stations, workplaces, and residence) contribute to pandemic transmission most, as they are places where individual contacts occur frequently; they are followed by infectious sources and travel mode. Second, commuting via public transit is a potential risk in most cities. This finding is vital for reminding citizens to strictly adhere to preventative measures when commuting via public transit, such as the wearing facemasks and maintaining social distancing. Third, walking is not as safe as the general public perceives even with an increased rate of facemask wearing. Even in urban areas with low population density, pedestrians were exposed to a higher infection risk when they ignored the suggested preventative measures. Fourth, driving is the safest way to commute among the three travel modes, as drivers have little risk of being in close contact with strangers.

Conflict of interest

The authors declare that they have no conflict of interest.

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Author contributions

Rui Zhu, Luc Anselin, Michael Batty, Mei-Po Kwan, Min Chen, and Carlo Ratti designed research; Rui Zhu, Wei Luo, and Tao Cheng performed research; Rui Zhu, Che Kang Lim, and Paolo Santi analysed data; Rui Zhu and Kai Zhang contributed data collection and processing; and Rui Zhu, Min Chen, Cheng Cheng, Qiushi Gu, Man Sing Wong, and Guonian Lü wrote the paper.

Appendix A. SM

Supplementary materials to this article can be found online at the Appendix.

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