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

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Previous studies have been focused primarily on modelling and predicting the transmission of COVID-19 ¹⁻³. While little research has been conducted to understand the impacts of different travel modes on the transmission of COVID-19, without an explicit understanding of the travel mode effects, many people intuitively perceive non-motorized travel modes to be safer than public transit as passengers in public transit are confined to small, enclosed spaces ⁴ where the virus can transmit more easily. During the period when urban mobility gradually returns towards what was called ‘normal’ and transit systems and urban facilities reopen, new waves of the pandemic might be generated as travel mode choices significantly differ across cities and different travel behaviors are associated with diverse infectious

43 sources ⁵. Thus, the current study focuses on understanding the impact of different travel
44 modes on the transmission of COVID-19 in the *long-term* and at *world-wide* scales, aspects
45 that have not received much attention in the research literature. Accordingly, a multivari-
46 ate time series analysis has been developed to examine the impacts of daily confirmed cases
47 and travel modes, based on driving, public transit, and walking as recorded in the Apple
48 Mobility Trends Reports on COVID-19 transmission risks in 71 cities throughout the world
49 from January to November 2020. The impact of population density in built-up areas and the
50 degree to which the ‘wearing’ of facemasks affects infections are also investigated. Among
51 the three travel modes we examine, driving is the safest way to commute because drivers
52 are physically separate from crowds. Unexpectedly, walking has a relatively low risk when
53 the population density in built-up areas is high, which suggests that, globally, people have
54 increased awareness of pandemic prevention. Although the general public is more worried
55 about using public transit, this mode can still be safe in many large cities, a factor that is vi-
56 tal for informing policy making and developing trust among citizens so they will continue to
57 commute using public transit when strict preventative measures are in place. From another
58 perspective, infectious sources make the largest contribution to daily confirmed cases, thus
59 demonstrating the importance of strict quarantine measures to block the source of infection.
60 The results and conclusions presented herein are based on an analysis of spatio-temporal
61 data that helps inform policy making and enable cities to be kept open when controlling the
62 pandemic, which has become an urgent task for the international community when rebuild-
63 ing the economy.

64 The outbreak of SARS-CoV-2 has led to more than 100 million confirmed cases and 2 mil-
65 lion deaths worldwide as of January 31, 2021 ⁶. The international community has made significant
66 efforts to flatten the COVID-19 curve, including executing unprecedented global lockdowns ^{7,8},
67 the promotion of the wearing of masks, and social distancing ^{9–11}, isolating confirmed cases and
68 contacts ¹², predicting transmission ¹³, and strengthening research collaboration in academia ¹⁴. In
69 fact, some countries appear to have stabilized their COVID-19 statistics by enforcing strict lock-
70 down measures since March 2020 ^{15,16}. Because of the adverse consequences caused by lockdown
71 measures ¹⁷, many cities have had to reopen so they can rebuild their economies. However, as
72 mobility has gradually returned towards normal, imported cases from unknown sources have dis-
73 rupted the recovery situation, and cities were at high risk of a new wave of outbreak ¹⁸. Thus, it
74 is imperative to quantify the effect of travel modes (i.e., driving, public transit, and walking) on
75 pandemic transmission so the pandemic can be controlled, especially during the reopening period
76 when mobility progressively returns towards normal.

77 Many studies have observed the effectiveness of lockdown measures to control the pan-
78 demic ^{7,8}, and such control measures have led to a dramatic reduction in urban mobility associated
79 with the transformation of travel behavior. Unlike studies that focus on the effect of COVID-19
80 on changes in mobility ¹⁹, this study aims to investigate the transmission of the pandemic asso-
81 ciated with travel modes and reveals tremendous heterogeneity at the global scale, which has not
82 been addressed by other studies that have considered the effects of mobility ^{2,20,21}. By particularly
83 focusing on urban mobility, one epidemiological study has suggested that the transmission risk
84 associated with public transportation, such as in trains with confined spaces, can lead to changes

85 based on travel time and seat location, with the highest risk found among passengers adjacent to
86 an infected patient ²².

87 However, it still remains unclear how different travel modes (e.g., driving, public transit, and
88 walking) affect the transmission of COVID-19, and understanding this is crucial for people who
89 make frequent commutes as part of their daily lives. Without rigorous studies, the population at
90 large and even some governments will continue to believe that private cars and nonmotorized mo-
91 bility (e.g., walking and cycling) are absolutely free from the transmission of the novel coronavirus,
92 thus making metros and buses the least popular travel modes during the pandemic ²³. For people
93 in cities such as Hong Kong and Singapore relying heavily on public transit, this vague perception
94 may also cause new waves of the pandemic because the transmission via travel modes can vary
95 significantly between different cities; for example, these might be associated with symptomatic
96 and asymptomatic carriers, travel behaviors, and populations of different gender, age, and ethnic
97 grouping ²⁴. Thus, it is crucial to quantify the effect of travel modes on daily confirmed cases at a
98 global scale to inform policy making and to provide useful guidance regarding safe forms of transit
99 for the general public.

100 To quantify the travel mode effect, this study developed a vector auto-regression model
101 (VAR) incorporating a time series of daily confirmed cases (c), daily proportions of those driv-
102 ing (d), those using public transit (t), and individuals walking (w), applying the model to each of
103 the 71 cities in 35 countries from January 13, 2020 to November 25, 2020 (Fig. 1a, see Meth-
104 ods). The values calculated by the autocorrelation function are significantly greater than 0.2 at the

Figure 1: The Granger causality matrix between the four variables in worldwide cities. **a**, The study investigates 71 cities in 35 countries across the continents of America, Asia, Africa, Europe, and Oceania. **b**, One variable is the Granger-causality of the other three variables when the p values are less than 0.05. The gray tiles are *null* due to missing information in the original data set.

105 25th percentile such that the four variables exhibit stable persistence in most cities ([Extended Data](#)
106 [Fig. 1](#)). Furthermore, none of the four variables in any of the 71 cities show any structural breaks
107 in the residuals, as none of the stability curves exceed the upper and lower confidence intervals
108 according to the R-based stability test. However, for nine cities (12.68%), the null hypothesis is
109 rejected, and thus, we conclude the presence of heteroscedasticity (i.e., the ARCH serial correlation
110 effect that clusters volatility areas in a time series) with $p < 0.05$. These cities include Buenos
111 Aires, Delhi, San Diego, Houston, Los Angeles, Madison, Mexico City, Phoenix, and Tel Aviv.

112 The vast majority of the 71 cities revealed an optimal lag at seven days (but note that for
113 Manila and Riyadh it was six days) based on the four indicators of the Akaike information criterion,
114 Hannan-Quinn criterion, Schwarz criterion, and the final prediction error, which is the same as the
115 longest incubation period, i.e., 5.2 days, with a 95% confidence interval (CI) between 4.1 and 7.0
116 days ²⁵. As some people are asymptomatic carriers ²⁶, this also indicates that they may adopt the
117 same travel behavior during the incubation period before they tested positive. Since the level of
118 urban mobility can spread the infection and simultaneously, the pandemic can influence the rates of
119 travel modes, a Granger-causality analysis is performed to determine the causality of one variable
120 on another ([see Methods](#)). It is found that driving (93.0%), public transit (94.4%), and walking
121 (93.0%) have a Granger-causality of daily confirmed cases ($p < 0.05$), and these cases are the
122 Granger-causality of itself in 47.9% of the cities ([Fig. 1b](#)). The findings suggest that travel modes
123 are an important means of pandemic transmission.

124 Furthermore, we calculate the changes in daily confirmed cases (Δc) caused by a positive

125 shock on each of the three travel modes using the impulse response function (IRF) with 100 it-
126 erations and a 95% CI ([Extended Data Figs. 2–6](#)), which allows us to test the impacts of the
127 travel modes on daily confirmed cases using mean and standard errors. Overall, driving and walk-
128 ing have the same influence rates in that they accelerate and decelerate the infection in an equal
129 number of cities (33 cities, 46.5%) (Figs. [2a](#), [2c](#)), but excluding five cities (7.0%) indicate no rela-
130 tionship based on the Granger-causality results. In contrast, the corresponding influence of public
131 transit occurs in 34 (47.9%), 20 (28.2%), and 17 cities (23.9%), respectively (Fig. [2b](#)). Finally,
132 the standard errors are significantly smaller in most cities, which suggests the results exhibit high
133 reliability.

134 This figure reveals four critical findings. First, public transit causes more disease spreading
135 than driving and walking. It is assumed that passengers in public transit (e.g., buses and metros)
136 are confined to small, enclosed spaces, which makes it challenging to maintain the one-meter-
137 plus social distancing rule. Public transit in Barcelona, Helsinki, Oslo, Paris, Prague, and Tokyo
138 stimulates the daily confirmed cases (Fig. [2b](#)), while driving and walking suppress cases (Figs. [2a](#),
139 [2c](#)). However, this does not mean that non-motorized travel modes are always safer than public
140 transit. For example, public transit in Chicago, Miami, New York City, Pittsburgh, Singapore,
141 Vancouver, and Washington DC can be safer than walking (Figs. [2b](#), [2c](#)), which indicates the
142 possibility that some people have a strong awareness of self-protection in enclosed spaces, that
143 policy restricts the number of people in public transit, and that there is increased disinfection
144 activity in these areas. Moreover, when looking at the largest four cities affected by each travel
145 mode, they have all confronted extremely difficult pandemic situations in 2020. This suggests

Figure 2: The mean changes (the barcharts) and standard errors (the horizontal black lines) of the daily confirmed cases subject to a positive shock of the three travel modes, as calculated by the IRF. **a**, Changes caused by a unit shock of driving. **b**, Changes caused by a unit shock of public transit. **c**, Changes caused by a unit shock of walking.

Figure 3: Contribution of infectious sources (VDs) to daily confirmed cases. The red dashed lines divide the box plots when the 25th percentile of VDs is larger than 0.8, between 0.5 and 0.8, and smaller than 0.5. 22 (40.8%), 20 (37.0%), and 12 (22.2%) cities are in the three groups, respectively.

that urban mobility can be a major transmission route in Delhi, Frankfurt, Indianapolis, London, Lyon, Madrid, Seattle, Stockholm, and Sao Paulo. Finally, all travel modes promote pandemic transmission in some cities (e.g., London, Leeds, Manchester, Budapest, Madison, and Ottawa). At the same time, all travel modes suppress transmission in five cities (i.e., Los Angeles, Mexico City, Montreal, Rio de Janeiro, and Toronto), which suggests that there are other external causes apart from travel modes.

In the IRF, Δc caused by the three travel modes are of different orders of magnitude. To compare the impacts of travel modes 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. Overall, $\{v_c\}$ decreases and $\{v_d, v_t, v_w\}$ increase with an increase in runs (Extended Data Figs. 7–10). Thus, the 25th percentile

157 of v_c (Fig. 3) and the 75th percentile of $\{v_d, v_t, v_w\}$ (Fig. 4) reveal their stable impacts on c . This
 158 indicates that an infectious source is a major influential factor that contributes to n_t in 22 cities
 159 (40.8%) with $v_c > 0.8$ (Fig. 3), which suggests that strictly controlling the infectious sources
 160 should be considered an urgent measure. Urban mobility is also a significant factor for coronavirus
 161 transmission in 12 cities (22.2%) with $v_c < 0.5$. Coincidentally, several cities have suffered from
 162 severe pandemic rates throughout the year, including Paris, Washington DC, and Boston.

163 The normalized VDs of the three travel modes allow us to make a direct comparison when
 164 only considering urban mobility impacts, presenting the conclusion that walking exhibits the
 165 largest contribution to c in 44.4% of the cities (Fig. 4c) followed by public transit (37.0%, Fig. 4b)
 166 and driving (20.4%, Fig. 4a) when their VD is larger than 0.5. The corresponding figures are
 167 53.7%, 25.9%, and 26.0%, respectively, when the VD is less than 0.2. Fig. 4 displays the four phe-
 168 nomena. First, driving is the safest travel mode given that, in general, v_d is smaller for driving than
 169 for the other two modes. A reasonable explanation is that drivers effectively separate themselves
 170 from strangers, thus minimizing their chance to be infected. Second, unlike the previous notion
 171 that public transit, such as metros and buses, always spread the pandemic to a wider and deeper
 172 degree because of its spread in small, enclosed spaces, the transmission via public transit depends
 173 on specific situations. Third, walking is an infectious travel mode in approximately half of the
 174 cities, which is likely beyond people's intuitive expectations. Fourth, different cities behave differ-
 175 ently with respect to their functionality of different travel modes. For example, some cities (i.e.,
 176 Manila, Rotterdam, Zurich, and Lyon) are significantly impacted by public transit. In other cities
 177 (i.e., Helsinki, Ottawa, San Diego, and Washington DC), the three travel modes contribute equally

Figure 4: Normalized VDs for the three travel modes with respect to daily confirmed cases. The red dashed lines divide the box plots when the 75th percentile of VDs is larger than 0.5, between 0.2 and 0.5, and smaller than 0.2. **a**, For driving, 11 (20.4%), 14 (25.9%), 29 (53.7%) cities are in the three groups. **b**, For public transit, 20 (37.0%), 20 (37.0%), 14 (26.0%) cities are in the three groups. **c**, For walking, 24 (44.4%), 16 (29.6%), 14 (26.0%) cities are in the three groups.

Figure 5: The Pearson correlation coefficients (R , $p < 0.05$) between the rate of wearing facemasks (k_t) and the change of the daily confirmed cases per mobility unit ($\Delta\rho_i$). w , t , and d in the y-axis present *walking*, *public transit*, and *driving*. $p1$ is the first period between January and May, and $p2$ is the second period between June and November. The grey tiles are due to no significant correlation.

to infections. Furthermore, the four largest cities where walking mainly contributes to infections (i.e., Pittsburgh, Phoenix, Madison, and Boston) are all in the U.S.

We consider that mask-wearing may mitigate transmission by controlling the confirmed cases via different travel modes. Therefore, the study has investigated the correlations between the rate at which facemasks are worn (k_t) associated with the mobility and the change of the confirmed cases per mobility unit ($\Delta\rho_i$) with an optimal seven-day lag. For cities with a significant correlation ($p < 0.05$), this analysis suggests that most cities (78%) obtain strong positive correlations for the three travel modes during the first period ($p1$), i.e., between January and May, and that all the cities exhibit a weak positive correlation during the second period ($p2$), i.e., between June and November

Figure 6: The Pearson correlation coefficients (R , $p < 0.05$) between the population density in built-up areas (d in the x-axis) and the changed cases (Δc in the y-axis) derived from the IRF. **a**, Δc caused by a shock of driving has no significant correlations with d . **b**, Δc caused by a shock of public transit has no significant correlations with d . **c**, Δc caused by a shock of walking has weak negative correlations with d .

(Fig. 5). The observation suggests that wearing facemasks could suppress the transmission across global cities during the early stage of the pandemic outbreak and that wearing facemasks remains effective even as the situation worsens, with the rate of wearing facemasks increasing continuously during the second half-year of the pandemic. However, seven cities derive negative correlations during the first period, and all of these cities are in the U.S. This suggests that wearing facemasks is ineffective in these cities, which may be due to a lack of awareness regarding social distancing and a refusal to follow the established or suggested quarantine measures.

Finally, there are no significant correlations between the population density in built-up areas (d) and the changed daily confirmed cases (Δc) obtained from the IRF of driving (Fig. 6a) and public transit (Fig. 6b). This means that d does not affect the transmission of the pandemic via

197 driving and public transit, which is reasonable given that these two travel modes create an isolated
198 environment such that the density can vary from the overall population density in the administra-
199 tive areas. In contrast, d and Δc for walking exhibit weak negative correlations with $R = -0.36$
200 ($p = 0.0387$) when $\Delta c > 0$ and $R = -0.44$ ($p = 0.0104$) and when $\Delta c < 0$ (Fig. 6c). The un-
201 expected negative correlations mean that higher population densities tend to transmit fewer cases
202 or restrain more cases. This indicates that even in cities with high population densities, people can
203 still commute safely by walking. Reasonable explanations for this may be that they have estab-
204 lished a wide consensus with respect to self-protection by, for example, reducing social contacts,
205 avoiding rush hours, maintaining social distances and wearing facemasks. However, people are
206 still somewhat unaware of the need for self-protection in cities with low population densities, and
207 walking is thus a non-negligible route of transmission.

208 This study emphasizes that the number of daily confirmed cases is influenced by mobility
209 behavior, but the logic can also run in the other direction such that mobility behavior can be af-
210 fected by the seriousness of COVID-19 infections. Thus, a multivariate time series analysis is used
211 because of this endogeneity in the causal directionality. As the situation worsens, more people stay
212 home, which is reflected by decreased mobility with respect to the baseline on January 13, 2020
213 (see Methods). One general observation is that there was a move from public transit to private
214 transit against an overall decrease in mobility. However, this effect is not modelled as the data
215 cannot reveal this transformation. The study does not consider the age-dependent effects²⁷ or the
216 death toll²⁸ because it is influenced by other factors, such as medical care conditions, the ability
217 of the health services to respond to the intensity of the pandemic and the ability of the system to

218 provide sufficient intensive care capacity.

219 This study’s underlying assumption is that the number of infectious spreaders can be ap-
220 proximated by the number of people who have tested positive. An alternative would be to take
221 the positive rate as a fraction of the persons tested and apply this to the total population to get a
222 sense of how many may be infected. However, both methods ignore the widely different testing
223 rates and testing policies in the different cities, which may bias the severity of the infection and
224 its relation to mobility. When defining the daily confirmed cases per mobility unit ($\rho_i = \frac{c}{m_i}$), the
225 infection is scaled by the three mobility rates. Essentially, this assumes that spreaders have an even
226 distribution across the three travel modes, but this is a speculation that has not yet been borne out
227 in practice.

228 Currently, eliminating the pandemic is challenging as new waves of the pandemic have al-
229 ready swept the world, cases of secondary infections have been reported ²⁹, and the validity of the
230 many vaccines are still under investigation. Thus, it is crucial to investigate the effect of travel
231 modes on the transmission of COVID-19 at the city level, which reveals the significance of our
232 study in providing practical safe commuting guidance for rebuilding the economy during the pe-
233 riod when lockdowns are released. Our study utilized the *Mobility Trends Reports* data from Apple,
234 which is an approach based on crowd-sourcing. Accordingly, this may cause a certain bias from
235 the entire travel modes in each city as evidenced based on our statistics from the Apple market
236 sharing in the 35 countries involved in the study ([Extended Data Fig. 11](#)). Nevertheless, the es-
237 sential findings obtained from the study are reliable in that they are derived from mathematical

238 modelling with considerable statistical significance.

239 Our study is significant in light of the widespread misconceptions about the travel modes’
240 effects on pandemic transmission. First, the study finds that public transit is still safe in some
241 cities. As people in cities such as Singapore heavily rely on public transit, it is almost impossible
242 to immediately transform the landscape of the transit system during the reopening period, as it
243 involves an overwhelming use of private cars. This finding is vital for informing policy making
244 and encouraging citizens to trust public transit and continue to use it to commute while strictly
245 adhering to preventative measures such as the wearing of facemasks when there are only a few
246 community infections. Second, walking is not as safe as the general public intuitively expects even
247 with an increasing rate of facemask wearing. During 2020, people in high population density areas
248 were supposed to have an increased their awareness of pandemic prevention in making walking
249 a relatively safe activity. Even in urban areas with a low population density, pedestrians were
250 exposed to a higher infectious risk when they ignored suggested preventative measures. Third,
251 driving is the safest way to commute among the three travel modes, as drivers have little risk of
252 being in close contact with strangers.

253 The results suggest that wearing facemasks is an effective way of controlling infectious
254 sources and reducing the transmission of COVID-19 via the three travel modes in many cities
255 (Fig. 5). The seven exceptional cities in the first period are all in the U.S., and they all change
256 to non-significant or positive correlations during the second period of the pandemic. This means
257 that facemasks become effective with an increase in the wearing rates when people commute by

the three travel modes even though the impact has not been as substantial as in the first period. In addition, with COVID-19 having swept the world for the last year, it is apparent that the high population density in built-up areas is not the cause of transmission when people have an increased awareness of self-protection. Accordingly, this finding reminds people of procedures, protocols and regulations concerning personal protection (e.g., the wearing of facemasks) when walking in both high and low density population areas.

Methods

Data collection and processing. We selected 71 global cities, including 29 cities in Europe, 26 in America, 12 in Asia, two in Oceania, and two in Africa. The *COVID-19 – Mobility Trends Reports* from Apple Inc. provide daily mobility changes in percentages subject to the baseline on January 13, 2020³⁰, thus reflecting requests for directions in Apple Maps during the COVID-19 pandemic. The collected data have been anonymized and aggregated into three categories, i.e., driving, public transit, and walking, which represent the major travel modes in the global cities. The COVID-19 daily confirmed cases in the cities were mainly collected from the COVID-19 dashboards of the local governments, although some were collected from GitHub and Wikipedia, albeit the data published in these sources were also released by various governments ([Supplementary Table 1](#)). A centred simple moving average with a width of five days is used to smooth vibrations and fluctuations in the original data set. Both the mobility data and the COVID-19 data were collected from January 13, 2020 to November 25, 2020. Since each travel mode is a relative indicator that disregards the proportion of all the travel modes, it must be rescaled by incorporating the travel

mode's rate in each city, thereby allowing us to investigate the impact of each mode on COVID-19. Thus, the travel modes' rates were collected from various sources, such as the Global BRT data produced in June 2020 and the Passenger Transport Mode Shares in World Cities produced in 2011 (Supplementary Table 2).

WorldPop provides the population density for 2020 with a spatial resolution of 1 km², which may cause significant bias as people in built-up areas may be concentrated in a small area out of each 1 km² zone. Therefore, the administrative boundaries of the cities were collected from GADM, and the built-up areas were derived from the global land cover data with a 30-meter spatial resolution. Based on this, the total population and the total built-up area within the boundaries of each city were computed so that the population density in the built-up area could be estimated, as it is deemed more reliable than obtaining data directly from WorldPop. The rates of wearing facemasks were collected from YouGov, and Apple's market share data for the 35 corresponding countries in June 2020 were obtained from StatCounter.

Constructing the mobility for the three travel modes. Let $M' = \{m'_d, m'_t, m'_w\}$ denote the proportions of the three major travel modes, i.e., driving, public transit, and walking, respectively, on day t subject to a baseline of January 13, 2020 in any global city, which follows the data structure established by Apple. Since the daily mobility $m'_i \in M'$ is essentially a relative indicator, by using the rates of the three mobilities $\{r_i\}$ on the baseline, the daily *dynamic mobility* can be calculated as $m_i = m'_i \cdot r_i$ ($m_i \in M$) to investigate their impacts on pandemic transmission.

297 **Multivariate time series analysis.** The overall analytical strategy quantifies the effects of travel
 298 modes M on daily confirmed cases c , allowing for a multivariate time series analysis. Specifically,
 299 a vector autoregression (VAR) model is built to capture the relationship between the four variables,
 300 i.e., $V = \{c, m_d, m_t, m_w\}$, in each city over time. In the model, each $v \in V$ is a linear function of
 301 past lags of itself and other variables, in which the past lags of c can be viewed as infectious sources
 302 that also effects daily confirmed cases. Furthermore, as a statistical hypothesis test, the Granger-
 303 causality (GC) test is conducted to determine whether one variable is useful to predict another so
 304 that we can examine the causality of one variable with respect to the other three variables. Then,
 305 the impulse response function (IRF) is used to investigate the changes of daily confirmed cases
 306 (Δc) in a subsequent period caused by a positive shock of each of the three travel modes. Finally,
 307 the variance decomposition (VD) is computed to determine the proportion of Δc explained by each
 308 of the variable in V so their impacts are comparable across different cities.

309 **Pearson correlation analysis.** It is supposed that the population density in the built-up areas
 310 (d_p) is an exogenous variable that influences Δc in the IRF, and that this is a direct indicator
 311 of people's awareness and practice of social distancing as explained by the Pearson correlations
 312 between d_p and Δc . Additionally, the rate of wearing facemasks (k_t) is not incorporated into the
 313 VAR because k_t is obtained from a survey with a discrete-time series that covers only part of the
 314 cities. Alternatively, an instrumental variable is defined as the changes of daily confirmed cases
 315 per mobility unit ($\Delta \rho_i = \rho'_i - \rho_i$) with an optimal time lag, where $\rho_i = \frac{c}{m_i}$ and ρ'_i is the intercept
 316 of a linear regression between k_t and ρ_i that satisfies the least squares. In such a case, Pearson
 317 correlations with the second least squares can be made between k_t and $\Delta \rho_i$.

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Figure 1: Persistence of the four variables calculated by the auto-correlation function (ACF).

(a,b,c,d) Persistence of the daily confirmed cases and the rates of driving, public transit, and walking, which are denoted by p_i , p_d , p_t , and p_w , respectively. Values in $[0.2, 1]$ are with 95% CI.

Figure 2: Changes of daily confirmed cases with a positive shock of driving in the IRF with 100 runs (part 1). The red curves are the 95% CI.

Figure 3: Changes of daily confirmed cases with a positive shock of driving in the IRF with 100 runs (part 2). The red curves are the 95% CI.

Figure 4: Changes of daily confirmed cases with a positive shock of transit in the IRF with 100 runs. The red curves are the 95% CI.

Figure 5: Changes of daily confirmed cases with a positive shock of walking in the IRF with 100 runs (part 1). The red curves are the 95% CI.

Figure 6: Changes of daily confirmed cases with a positive shock of walking in the IRF with 100 runs (part 2). The red curves are the 95% CI.

Figure 7: VDs of infection for daily confirmed cases with 100 runs.

Figure 8: VDs of driving for daily confirmed cases with 100 runs.

Figure 9: VDs of public transit for daily confirmed cases with 100 runs. Cities without curves are due to missing information in the original data set.

Figure 10: VDs of walking for daily confirmed cases with 100 runs.

Figure 11: The percentage of the Apple market sharing in the 35 countries/regions in 2020.

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Supplementary Information
The effects of different travel modes on COVID-19 transmission in global cities

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Table 1. Source of the pandemic data that was lastly accessed on December 1, 2020.

No.	Country	City	Author	Title
1	Argentina	Buenos Aires	Wikipedia	Template: COVID-19 Pandemic Data/Argentina Medical Cases
2	Australia	Sydney	NSW Government	COVID-19 Cases by Notification Date, Location
3	Austria	Vienna	Days since	Days Since
4	Belgium	Brussels	Sciensano	COVID-19 Belgium Epidemiological Situation Summary
5	Brazil	Rio de Janeiro	Coronavirus/Brasil	COVID-19 Panel Coronavirus
6	Brazil	Sao Paulo	Coronavirus/Brasil	COVID-19 Panel Coronavirus
7	Canada	Calgary	Alberta	COVID-19 Alberta Statistics
8	Canada	Montreal	GitHub	COVID-19 Cases in Montreal
9	Canada	Ottawa	Ottawa Public Health	Ottawa's COVID-19 Dashboard
10	Canada	Toronto	Toronto	COVID-19: Status of Cases in Toronto
11	Canada	Vancouver	GitHub	British Columbia COVID-19 Dashboard
12	China	Hong Kong	The Hong Kong Government	COVID-19-Data
13	Czech Republic	Prague	Current disease	COVID-19 in the Czech Republic: Open Data Sets and Downloadable Sets
14	Finland	Helsinki	GitHub	Finnish Coronavirus Infections Are Public Data
15	France	Lyon	Ministry of Solidarity and Health and Public Health France	COVID-19 - France
16	France	Paris	Bing	Paris
17	Germany	Berlin	Kaggle	COVID-19 Tracking Germany
18	Germany	Cologne	Robert Koch-Institut: COVID-19-Dashboard	Robert Koch-Institute: COVID-19-Dashboard
19	Germany	Frankfurt	Robert Koch-Institut: COVID-19-Dashboard	Robert Koch-Institute: COVID-19-Dashboard
20	Germany	Hamburg	Kaggle	COVID-19 There Has Been A Decline in Germany and Globally
21	Germany	Munich	Robert Koch-Institut: COVID-19-Dashboard	Robert Koch-Institute: COVID-19-Dashboard

22	Germany	Stuttgart	Robert Koch-Institut: COVID-19-Dashboard	Robert Koch-Institute: COVID-19-Dashboard Information Page About Coronavirus
23	Hungary	Budapest	Koronavirus.gov.hu	India
24	India	Delhi	Covid19india	Mumbai
25	India	Mumbai	Azure	Covid-19 Monitoring Data
26	Indonesia	Jakarta	COVID-19 Emergency Service	Ireland's COVID-19 Data Hub
27	Ireland	Dublin	COVID-19 Ireland	The Database
28	Israel	Tel Aviv	Data Gov Government Database	COVID-19 in Italy
29	Italy	Milan	Kaggle	COVID-19 in Italy
30	Italy	Rome	Kaggle	COVID-19 Dataset in Japan
31	Japan	Osaka	Kaggle	COVID-19 Dataset in Japan
32	Japan	Tokyo	Kaggle	COVID-19 By State in Malaysia
33	Malaysia	Kuala Lumpur	Department of Statistics Malaysia	General Information
34	Mexico	Mexico City	Government of Mexico	COVID-19 Cumulative Figures Per Municipality
35	Netherlands	Amsterdam	RIVM Data Catalogus	COVID-19 Cumulative Figures Per Municipality
36	Netherlands	Rotterdam	RIVM Data Catalogus	COVID-19 Cumulative Figures Per Municipality
37	Netherlands	Utrecht	RIVM Data Catalogus	COVID-19-Current Cases Details
38	New Zealand	Auckland	Ministry of Health	COVID-19 Pandemic in Norway
39	Norway	Oslo	Azure	COVID-19 Case Tracker
40	Philippines	Manila	Republic of the Philippines Department of Health	Template: COVID-19 Pandemic Data/Russia Medical Cases
41	Russia	Moscow	Wikipedia	The National Health Emergency Operation Center NHEOC
42	Saudi Arabia	Riyadh	Covid19 Data and Informatics Committee	Real-time Outbreak in Singapore
43	Singapore	Singapore	Tencent news	Provinces
44	South Africa	Cape Town	Coronavirus SA Data	Provinces
45	South Africa	Johannesburg	Coronavirus SA Data	Coronavirus Disease-19, Republic of Korea
46	South Korea	Seoul	Azure	Barcelona's City Hall Open Data Service
47	Spain	Barcelona	Open Data BCN	

48	Spain	Madrid	Madrid Community	Status Report for 30 November 2020
49	Sweden	Stockholm	Wikipedia	Template: COVID-19 Pandemic Data/Sweden Medical Cases
50	Switzerland	Zurich	OpenZH	COVID-19 Information for Switzerland
51	Thailand	Bangkok	Data.go.th	Daily COVID-19 Reports
52	UK	Birmingham - UK	GOV.UK	Coronavirus(COVID-19) in the UK
53	UK	Leeds	GOV.UK	Coronavirus (COVID-19) in the UK
54	UK	London	Wikipedia	COVID-19 Pandemic in London
55	UK	Manchester	GOV.UK	Coronavirus (COVID-19) in the UK
56	US	Atlanta	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
57	US	Boston	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
58	US	Chicago	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
59	US	Houston	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
60	US	Indianapolis	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
61	US	Las Vegas	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
62	US	Los Angeles	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
63	US	Madison	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
64	US	Miami	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
65	US	New York City	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University

66	US	Phoenix	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
67	US	Pittsburgh	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
68	US	San Diego	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
69	US	Santa Barbara	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
70	US	Seattle	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University
71	US	Washington DC	COVID-19 Dashboard by the CSSE at Johns Hopkins University	COVID-19 Dashboard by the CSSE at Johns Hopkins University

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Table 2. Sources of urban mobility data that was lastly accessed on October 9, 2020.

No .	Country	City	Author	Title	Data produce year
1	Argentina	Buenos Aires	Omu.caf.com	Global BRT Data	2012
2	Australia	Sydney	CLC & ULI	Urban Mobility: 10 Cities Leading the Way in Asia-Pacific	2015
3	Austria	Vienna	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2013
4	Belgium	Brussels	Wikipedia	Modal Share	2010
5	Brazil	Rio de Janeiro	Political School	Federal University of The Janeiron River	2012
6	Brazil	Sao Paulo	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2012
7	Canada	Calgary	Wikipedia	Modal Share	2016
8	Canada	Montreal	Wikipedia	Modal Share	2016
9	Canada	Ottawa	Wikipedia	Modal Share	2016
10	Canada	Toronto	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2011
11	Canada	Vancouver	Wikipedia	Modal Share	2016
12	China	Hong Kong	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2014
13	Czech Republic	Prague	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2013
14	Finland	Helsinki	Wikipedia	Modal Share	2016
15	France	Lyon	www.epomm.eu	Global BRT Data	2010
16	France	Paris	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2008
17	Germany	Berlin	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2013
18	Germany	Cologne	Wikipedia	Modal Share	2013
19	Germany	Frankfurt	Wikipedia	Modal Share	2015
20	Germany	Hamburg	Infas	Mobility in the Greater Hamburg Area	2008
21	Germany	Munich	Wikipedia	Modal Share	2017
22	Germany	Stuttgart	Wikipedia	Modal Share	2010
23	Hungary	Budapest	Wikipedia	Modal Share	2011
24	India	Delhi	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2010
25	India	Mumbai	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2011
26	Indonesia	Jakarta	Wikipedia	Modal Share	2019
27	Ireland	Dublin	Wikipedia	Modal Share	2016

28	Israel	Tel Aviv	2MOVE2	The Evolution of Cycling Patterns in Tel Aviv- past Experience and Future Trends International Seminar on Cycling Policies Milano, from Pollution Charge to Congestion Charge	2015
29	Italy	Milan	Azzer0CO2	Modal Share	2007
30	Italy	Rome	Wikipedia	Passenger Transport Mode Shares in World Cities	2014
31	Japan	Osaka	Nanopdf.com	Urban Mobility: 10 Cities Leading the Way in Asia-Pacific	2012
32	Japan	Tokyo	CLC & ULI	Mode Choice between Private and Public Transport in Klang Valley, Malaysia	2008
33	Malaysia	Kuala Lumpur	Chuen, O.C., et al.	Global BRT Data	2014
34	Mexico	Mexico City	www.oecd.org	Modal Share	2007
35	Netherlands	Amsterdam	Wikipedia	Modal Share	2014
36	Netherlands	Rotterdam	Wikipedia	Modal Share	2004
37	Netherlands	Utrecht	Wikipedia	Modal Share	2015
38	New Zealand	Auckland	NZ.Stat	New Zealand Household Travel Survey: Travel to Work, by Main Urban Area Results (3-Year Moving Average)	2014
39	Norway	Oslo	Wikipedia	Modal Share	2013
40	Philippines	Manila	Journeys	Passenger Transport Mode Shares in World Cities	2019
41	Russia	Moscow	Simon Dixon	Deloitte Insights	2019
42	Saudi Arabia	Riyadh	Riyadh Municipality	Deloitte City Mobility Index 2020	2020
43	Singapore	Singapore	CLC & ULI	Urban Mobility: 10 Cities Leading the Way in Asia-Pacific	2012
44	South Africa	Cape Town	www.statssa.gov.za	Global BRT Data	2014
45	South Africa	Johannesburg	www.joburg.org.za	Global BRT Data	2002
46	South Korea	Seoul	CLC & ULI	Urban Mobility: 10 Cities Leading the Way in Asia-Pacific	2015
47	Spain	Barcelona	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2012

48	Spain	Madrid	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2011
49	Sweden	Stockholm	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2012
50	Switzerland	Zurich	Planning office Jud, Zurich	Comparison of Cities Mobility	2015
51	Thailand	Bangkok	www.ide.titech.ac.jp	Global BRT Data	2009
52	UK	Birmingham - UK	Wikipedia	Modal Share	2001
53	UK	Leeds	Leeds City Council	Leeds Transport Strategy Interim December 2016	2016
54	UK	London	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2013
55	UK	Manchester	www.epomm.eu	Global BRT Data	2011
56	US	Atlanta	Census Reporter	Atlanta, GA Urbanized Area	2016
57	US	Boston	Census Reporter	Boston, MA-NH-RI Urbanized Area	2016
58	US	Chicago	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2008
59	US	Houston	Census Reporter	Houston, TX Urbanized Area	2016
60	US	Indianapolis	Census Reporter	Indianapolis, IN Urbanized Area	2016
61	US	Las Vegas	Census Reporter	Las Vegas-Henderson, NV Urbanized Area	2016
62	US	Los Angeles	Census Reporter	Los Angeles-Long Beach-Anaheim, CA Urbanized Area	2016
63	US	Madison	Carpool World	Commuting Mode Analysis Madison WI US	
64	US	Miami	Census Reporter	Miami, FL Urbanized Area	2016
65	US	New York City	Nanopdf.com	Passenger Transport Mode Shares in World Cities	2009
66	US	Phoenix	Census Reporter	Phoenix-Mesa, AZ Urbanized Area	2016
67	US	Pittsburgh	www.thetransportpolitic.com	Global BRT Data	2009
68	US	San Diego	Census Reporter	San Diego, CA Urbanized Area	2016
69	US	Santa Barbara	Carpool World	Commuting mode analysis Santa Barbara CA US	2020

70	US	Seattle	Census Reporter	Seattle, WA Urbanized Area	2016
71	US	Washington DC	Census Reporter	Washington, DC-VA-MD Urbanized Area	2016

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Figures

Figure 1

The Granger causality matrix between the four variables in worldwide cities. a, The study investigates 71 cities in 35 countries across the continents of America, Asia, Africa, Europe, and Oceania. b, One variable is the Granger-causality of the other three variables when the p values are less than 0.05. The gray tiles are null due to missing information in the original data set. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

The mean changes (the barcharts) and standard errors (the horizontal black lines) of the daily confirmed cases subject to a positive shock of the three travel modes, as calculated by the IRF. a, Changes caused by a unit shock of driving. b, Changes caused by a unit shock of public transit. c, Changes caused by a unit shock of walking.

Figure 3

Contribution of infectious sources (VDs) to daily confirmed cases. The red dashed lines divide the box plots when the 25th percentile of VDs is larger than 0.8, between 0.5 and 0.8, and smaller than 0.5. 22 (40.8%), 20 (37.0%), and 12 (22.2%) cities are in the three groups, respectively.

Figure 4

Normalized VDs for the three travel modes with respect to daily confirmed cases. The red dashed lines divide the box plots when the 75th percentile of VDs is larger than 0.5, between 0.2 and 0.5, and smaller than 0.2. a, For driving, 11 (20.4%), 14 (25.9%), 29 (53.7%) cities are in the three groups. b, For public transit, 20 (37.0%), 20 (37.0%), 14 (26.0%) cities are in the three groups. c, For walking, 24 (44.4%), 16 (29.6%), 14 (26.0%) cities are in the three groups.

Figure 5

The Pearson correlation coefficients (R , $p < 0.05$) between the rate of wearing facemasks (kt) and the change of the daily confirmed cases per mobility unit (Δp_i). w , t , and d in the y-axis present walking, public transit, and driving. p_1 is the first period between January and May, and p_2 is the second period between June and November. The grey tiles are due to no significant correlation.

Figure 6

The Pearson correlation coefficients (R , $p < 0.05$) between the population density in built-up areas (d in the x-axis) and the changed cases (ΔC in the y-axis) derived from the IRF. a, ΔC caused by a shock of driving has no significant correlations with d . b, ΔC caused by a shock of public transit has no significant correlations with d . c, ΔC caused by a shock of walking has weak negative correlations with d .