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Abrupt changes, institutional reactions, and adaptive behaviors: An exploratory study of COVID-19 and related events’ impacts on Hong Kong’s metro riders

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ABSTRACT

Abrupt socioeconomic changes have become increasingly commonplace. In face of these, both institutions and individuals must adapt. Against the backdrop of the COVID-19 pandemic, suddenness, scale, and impacts of which are unprecedented as compared to its counterparts in history, we first propose transferable measures and methods that can be used to quantify and geovisualize COVID-19 and subsequent events’ impacts on metro riders’ travel behaviors. Then we operationalize and implement those measures and methods with empirical data from Hong Kong, a metropolis heavily reliant on transit/metro services. We map out where those impacts were the largest and explores its correlates. We exploit the best publicly available data to assemble probable explanatory variables and to examine quantitatively whether those variables are correlated to the impacts and if so, to what degree. We find that both macro- and meso-level external/internal events following the COVID-19 outbreak significantly influenced of metro riders’ behaviors. The numbers of public rental housing residents, public and medical facilities, students’ school locations, residents’ occupation, and household income significantly predict the impacts. Also, the impacts differ across social groups and locales with different built-environment attributes. This means that to effectively manage those impacts, locale- and group-sensitive interventions are warranted.

1. Introduction

In past few decades, abrupt changes caused by economic and financial crises, social protests, terrorist attacks, and outbreak of pandemics/epidemics have become increasingly commonplace across countries and regions. Taking Hong Kong as an example, it has endured and/or is still enduring at least the following abrupt and shocking events and/or their derivatives: the 2003 SARS outbreak, the 2007/08 Asian Financial Crisis, the 2007 to 2010 Global Financial Crisis, the 2014 Umbrella Movement, the Anti-Extradition Upheavals (2019-present), and the COVID 19 pandemic (2020-present). In face of these, local institutions and individuals have undertaken many (unprecedented) countermeasures, which have profoundly affected their respective operations or behaviors.

As shown in the ensuing survey of existing literature, different authors have used various indicators and methods to measure and geovisualize travel behaviors of different social groups and market segments across different spatiotemporal scales. However, only recently have academics done so in extreme situations where there are large-scale health-related abrupt and shocking events such as COVID-19. Therefore, we still know little about which indicators and methods would be more relevant in those situations and how we should adapt existing or develop new indicators and methods to better identify and epitomize wide-ranging and lasting impacts of extreme situations.

In the existing literature, few also have taken advantage of non-traditional data such as smartcard data, which contain continuous and rich travel information about a much larger sample of transit riders than traditional data such as surveys or interviews. The information provided by non-traditional data includes but is not limited to: transit stops and stations that these riders have been to, ingress/boarding and egress/alighting times, type/amount of fares paid, route selected, distance travelled, and frequency of travel. In principle, by linking the information to other publicly available data such as census, land use, and transit network, one can efficiently:

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(a) operationalize indicators and/or visuals to quantify/compare travel behaviors of millions of transit riders by different spatiotemporal units of analysis before, amid, and after an abrupt event (e.g., COVID-19),
(b) fit quantitative models to predict impacts of the event on those behaviors and identify and/or verify their respective influencing factors, and
(c) based on the above indicators, visuals, and models, explore socioeconomic implications of corresponding (spatiotemporal) variations across subgroups of travelers.

In short, in the existing study, little has been done how to select, prioritize, and operationalize indicators and/or visuals based on both non-traditional and traditional data concerning adaptive travel behaviors and their variations across space and social groups given the occurrence of an abrupt event, especially COVID-19. This motivates us to (a) propose/adapt indicators and methods that are suitable for capturing impacts of COVID-19 and (b) demonstrate the relevance and usefulness of the proposed/adapted indicators by conducting an empirical study of Hong Kong’s metro riders’ adaptive behaviors at the metro station level and their predictors amid COVID-19.

Hong Kong is a typical high-density city where public transit carries the lion’s share (90%+) of passenger trips. If a shocking/aprupt event like COVID-19 and its derivatives influence the local society and economy, corresponding impacts can be more or less unfolded by looking at transit riders’ behaviors and related changes. Most notably, the significance and meanings of different locations in the city are to a large extent reshaped by its extensive and expanded transit network and services and the reliance and usage of residents on them (c.f., Bertolini, 1996; Cervero and Murakami, 2009). Against the backdrop of COVID-19, the above significance and meanings can greatly change when fewer people go out and/or use transit and/or when transit services are adjusted or suspended. For instance, when lots of white-collar workers rely more or more on virtual meetings, the local central business district is no longer a go out and/or use transit and/or when transit services are adjusted or suspended. For instance, when lots of white-collar workers rely more or more on virtual meetings, the local central business district is no longer a place for intensive face-to-face interactions as it did prior to the outbreak of COVID-19. Thus, transit riders’ behaviors and related changes amid COVID-19 provide a lens through which one can identify the impacts of a shocking/aprupt event on different riders across the space. When extra efforts are undertaken to quantify the sociodemographic attributes of the riders and how they are related to those impacts, we can also unravel how those impacts vary across different socioeconomic groups.

Specifically, we attempt to examine in this study:

(a) how residents, metro riders in particular, across different locales in Hong Kong have responded to the COVID-19 pandemic and subsequent or concurrent macro- and meso-level events, e.g., the Wuhan/Hubei lockdown and the local government’s working from home policy, which are unprecedented institutional reactions to a shocking/aprupt event?
(b) how different responses have reshaped activity and mobility patterns of metro riders, who constitute 37% of all the local transit patronage (Transport & Housing Bureau, 2017)?
(c) Which built environment, metro network, socioeconomic, and spatial factors can explain the spatiotemporal variations in mobility patterns of metro riders?
(d) In light of the above, what kind of (transferable) policy implications we can identify?

In our study, we exploit both non-traditional (big) data, especially Octopus (smartcard) data and traditional data (e.g., censuses, surveys, and land use maps) to investigate the change in metro riders’ travel pattern ex ante and ex post one remote/local event amid COVID-19. New or adapted indicators and visuals are introduced to quantify the pattern and its change at the metro station level. We hypothesize that metro station area (built environment) characteristics, metro station’s network features, sociodemographic characteristics, and increased health risk among people due to the outbreak of COVID-19 would all significantly predict the change. Fitting regression models between the change and its probable influencing factors and comparing the pattern ex ante and ex post an event would allow us to unravel the possible determinants of the pattern and its change. For instance, whether and to what degree the percentage of blue-collar workers around a metro station would predict the number/distribution of destinations among riders from that station after the introduction of the local working from home policy? Also, whether and to what degree a metro station’s centrality in the local metro network is correlated to the temporal concentration of incoming or outgoing trips of that station?

The remainder of the paper is organized as follows. The next section (Section 2) reviews existing literature on travel behaviors and their changes, synthesizing (a) which indicators and/or methods have been and can be used to measure and geovisualize adaptive behaviors among transit/metro riders and (b) research gaps one can fill in the existing literature. Section 3 introduces measures and methods proposed by the authors in light of the literature review to quantify or geovisualize (adaptive) behaviors among transit/metro riders pre- and post-a typical COVID-19-related event. Section 4 presents an empirical study in the context of Hong Kong. In this section, we illustrate how to measure and geovisualize the (adaptive) behaviors and related changes using real-world data. We also quantify which explanatory variable(s) would significantly influence metro riders’ travel behaviors and related changes at the metro station area level. Section 5 concludes.

2. Changes in travel patterns/behaviors

2.1. Changes in travel patterns/behaviors without abrupt events

Even without mega abrupt events such as COVID-19, there still can be observable changes in travel patterns and behaviors. Most studies prior to COVID-19 focus on these changes and how to quantify and geovisualize them. In the relatively stable pre-COVID-19 world, Zhao et al. (2018) illustrated there exists “abrupt, substantial and persistent changes” in travel behaviors, which can be quantified in three dimensions: the frequency of travel, time of travel, and origins/destinations. In face of abnormal natural events, e.g., extreme weather, De Palma and Rochat (1999) and Sabir et al. (2010) showed that trips can be re-scheduled, re-routed, and shifted to another mode. Corcoran and Tao (2017) adapted a method called “flow-comap” by Tao et al. (2014) to geovisualize the weather-transit usage relationship at the station-to-station level by hour of a day. Flow-comap can be used to identify and geovisualize probable trajectories of transit riders between origin-destination pairs. It is comparable to “desired lines” in travel demand modeling, which are the aggregated flows along the shortest path between centroids of two units of analysis, e.g., traffic analysis zone (Caliper, 2020).

At the route level, transit users can stick to the same route or choose multiple routes for any given pair of transit stations or stops. Kim et al. (2017) developed a stickiness index to quantify this, which they defined as the range of preferences of transit users in route selection for a given period. They believe that between the same pair of start and end stations/stops, there can be users who prefer the same route or few routes and those do not.

At the network/system levels, there could be “central places” for transit users, where there are the largest number of incoming or outgoing trips in few locales in a city or region across hours of a day or days of week. The number and distribution of central places, the origins and destinations of the trips to and from those places and associated desired lines can be used to simplify and characterize transit flows of a transit network across different temporal units. Using empirical data from Brisbane, Australia, Wei and Zhou (2016) showed the number and distribution of central places of local transit riders and their respective trip origins using a standard deviational ellipse. To identify those central places, they adapted the head-tail algorithm by Jiang (2013) which
“partitions all of the data values around the mean into two parts and continues the process iteratively for the values (above the mean) in the head until the head part values are no longer heavy-tailed distributed”. To map out the desired lines between those central places and trip origins, they assumed that transit riders always chose the shortest path between any pair of transit stations or stops.

Over a longer period and across spatial granularities, travel patterns of all travelers or a subset of them can remain stable or change significantly, which could have important socioeconomic and public policy implications (e.g., whether a subgroup of the population in a community consistently suffer from long commute). Hu et al. (2017) paid special attention to workers’ commuting time and distance variability and stability, using three sets of the US Census data between 1990 and 2010. As those data already aggregated commuters’ origins and destinations by census tract, estimating accurate distance can be a challenge because of aggregation error and scale effect. They thus proposed and implemented a Monte Carlo simulation of individual trips to address the challenge. Their analyses show that lowest-wage workers suffered from poor mobility. Their workplaces were in few isolated locations and their home or workplace tracts had few transport options.

2.2. Changes in travel patterns/behaviors amid abrupt events

Abrupt events are not exceptions in the world we live in. Prior to COVID-19, such events occurred too and notably impacted travel patterns/behaviors. In the existing scholarship, academics have examined the travel-related impacts of abrupt events such as the 911 terrorist attacks in the US (Blank et al., 2006; Ito & Lee, 2005) and the Occupy Central Movement (OCM) in Hong Kong (Loo & Leung, 2017). Their studies reconfirm that “large-scale disruptions caused not just by natural hazards but also human beings” (Loo & Leung, 2017, p. 100). In addition, the impacts of the disruption, including those on travel patterns/behaviors are multidimensional and across different spatiotemporal scales. Often, new indicators and methods are needed to quantify and ascertain those impacts. To better quantify, manage, and mitigate impacts of events such as OCM, for instance, Loo and Leung (2017) proposed Key Resilience Performance indicators for the local transport system. Blank et al. (2006) exploited the counter-factual forecast to ascertain whether the US domestic airline travel demand had restored to the average of normal years after the 911 terrorist attacks. Outside academia, there have also been many (online) narratives concerning travel impacts of social disruptions caused by abrupt civil unrests in Paris, London, and Hong Kong (e.g., Securewest International, 2021; The Major, 2019).

The outbreak of COVID-19 has engendered a series of publications on impacts of the pandemic on people’s travel and activities. These publications can be quickly identified through Google Scholar using key words such as COVID-19 and travel or mobility. They can be roughly categorized into two streams based on the input data used, corresponding indicators formulated, and what kind of information those indicators can convey and disclose. Stream 1 uses data from traditional sources such as surveys, which can better inform us about variations in the impacts across different social groups, modes of travel, and trip purposes. Beck and Hensher (2020), for instance, used survey responses to examine how the Australian government’s various COVID-19 containment measures influenced travel activity patterns of Australians. Their study shows what kind of households and activities and which mode of travel were affected more: Younger households still made significantly more trips than other households; Public transport suffered the most—people have a high degree of trepidation with this mode after COVID-19. In Istanbul, Shalikhei et al. (2021) conducted longitudinal and cross-sectional surveys after COVID-19 and found that trips of all purposes were significantly suppressed. Again, they found that public transport experienced a decline in both (short-term) attractiveness and patronage.

Stream 2 employs data from non-traditional sources such as social media, mobile phone location data, traffic control cameras, and public transport ITS, which often enables quantification and mapping of the impacts across more spatiotemporal units of analysis. Huang et al. (2020) used 580 million tweets to see how the single-day distance and the cross-day distance varied across countries at the global level and across states in the US. By exploiting mobile phone location data, Hara and Yamaguchi (2021) compared the travel behaviors before and after the official deceleration of COVID-19 outbreak in Japan. They found that the total number of trips decreased significantly, and population density index derived from the mobile phone location data was down 20%. Their findings are in general in line with those reported in other studies such as Jenelius and Cebecauer (2020) in Sweden and Teixeira and Lopes (2020) in New York. Jenelius and Cebecauer (2020) used a combination of traditional ticket validation and (non-traditional) automatic passenger counting sensor data. Teixeira and Lopes (2020) used data from local bike-sharing and subway databases. The bike-sharing database contained both bike usage and a little sociodemographic information concerning shared bike users at the individual level whereas the subway database provided only rider counts by station for each 4 h of a day.

2.3. Influencing factors of changes in travel patterns/behaviors

In existing studies, scholars have been investigating the explanatory factors that influence travel patterns/behaviors and their changes for decades. At some risk of oversimplifying the reality, there are approximately five groups of the explanatory factors that have been identified or extensively examined:

1. socio-demographic characteristics at the community level (Hanson, 1981; Pas, 1984; Goodchild et al., 1984),
2. land-use pattern or built-environment (Hansen, 1959; Boarnet & Sarmiento, 1998; Crane & Crepeau, 1998),
3. direct or indirect policies and transport strategies (Cervero, 1996; Meyer, 1999; Handy, 2005),
4. transport infrastructure and availability (Meyer, 1999; Handy, 2005), and
5. individual attributes and preferences (Hensher, 1994; Vogt, 1976).

In the existing studies, however, only few authors investigate how commuters alter their travel demand and preferred modes when facing some unplanned events, such as terrorist attacks (Prager et al., 2011; Rubin et al., 2007; Ito & Lee, 2005.) and earthquakes (Gray et al., 1990; Yashinsky, 1999). Given its sudden outbreak, COVID-19, related events, and their impacts on travel patterns have not been well studied. Emerging (and limited) studies, however, have indicated that the impacts can be widespread, significant, and long lasting. In Budapest, Hungary, trips of all modes of transport decreased significantly amid COVID-19, with public transit suffering from the greatest decline (Bucsky, 2020). In Hong Kong, MTR saw only 637 million passengers in the first half of 2020, down 38% from 2019. The decline resulted in HK$400 million net loss to MTR, a very rare occurrence since the 1970s (Yau, 2020).

In summary, the existing literature reviewed above indicates that changes in travel behaviors can occur regardless of there is an abrupt event like COVID-19 or not. Indicators and methods have been formulated to capture those changes. Most of those indicators and methods, however, are not tailored to measure and geovisualize the specific impacts of COVID-19 on travel behaviors. Little has been done to see which indicators and methods would be more appropriate than others to deal with those impacts. To the best knowledge of the authors, multiday smartcard data and its combination with other public available data such as census and point of interest data have also not been exploited to:
(1) measure and geovisualize the impacts of COVID-19 on travel behaviors at the metro station level,
(2) identify the spatial variation of those impacts,
(3) see whether and how sociodemographic and network attributes (e.g., centrality) of a metro station can predict the impacts, and
(4) whether and to what degree increased health risk among people because of the outbreak of COVID-19 would amplify the impacts.

There are research gaps that one can fill. In this study, we attempt to adapt and operationalize a few existing indicators and methods using empirical data to fill some of those gaps.

3. Measures and methods proposed and used

The outbreak of an abrupt shock like COVID-19 can have multidimensional impacts on different people in across locales. For a transit-reliant city like Hong Kong, many of those impacts can be identified should we formulate appropriate indicators and develop/adapt appropriate methods to measure or visualize the transit riders’ travel patterns before and after a COVID-19 related event. In this study, we argue that the total numbers of trips, the average distance/duration of trips, spatiotemporal distribution of trips’ departure/arrival times/destinations by metro station can be used to quantify some impacts of those events on transit/metro riders. For instance, after the Wuhan/Hubei lockdown, fewer people would go out and thus fewer transit trips would be observed. For those who still travelled, they might reduce their respective travel distances/durations to minimize the healthy risk posed by COVID-19. Riders would also do their best to avoid peak hours and congested destinations to keep reasonable social distancing.

Specifically, we propose the following six sets of indicators (or visuals) to measure and geovisualize different aspects of metro riders’ (adaptive) behaviors pre- and post-a special COVID-19 related event. We hypothesize that such event would affect the values of all those indicators and the variations in the values can be explained by sociodemographic, built environment, metro network, and spatial factors. For instance, metro services became less popular when a COVID-19-related event occurred thus most metro stations saw fewer incoming and outgoing trips. But there could be variations across stations and across rider demographic, built environment, metro network, and spatial factors. For instance, metro services became less popular when a COVID-19-related event occurred thus most metro stations saw fewer incoming and outgoing trips. But there could be variations across stations and across rider demographic, built environment, metro network, and spatial factors. For instance, metro services became less popular when a COVID-19-related event occurred thus most metro stations saw fewer incoming and outgoing trips. But there could be variations across stations and across rider demographic, built environment, metro network, and spatial factors. For instance, metro services became less popular when a COVID-19-related event occurred thus most metro stations saw fewer incoming and outgoing trips.

Incoming (A) and outgoing (P) trips by station per hour. These trips reflect how popular a station is to riders from other stations and how many riders from a station are enticed to other stations. We hypothesize that where there are more essential facilities (e.g., groceries and medical services) in or around a station, the station would be more popular amid COVID-19 and thus residents around the station would make fewer outgoing trips whereas the number of incoming trips would not significantly decrease. A and P are calculated using the following equations:

\[ A_i = \frac{\sum_{j=1}^{n} t_{ji} \cdot k_{ij}}{K_i} \]  
\[ P_j = \frac{\sum_{i=1}^{n} t_{ij} \cdot k_{ij}}{K_j} \]  

where.

\( t_{ij} \) is the incoming trips from Station j to Station i, \( k_{ij} \) is the number of stops/stations in the local transit/metro system; \( t_{ij} \) is the outgoing trips from Station i to Station j.

\( K_i \) is the total hours of operation at Station i or j, \( k_i \) and \( k_j \) can be the same or be different.

Average trip length (L) and average trip duration (D) for either A (or P).

The following formulas are used to calculate L and D:

\[ L_i = \frac{\sum_{j=1}^{n} t_{ji} \cdot d_{ij}}{A_i} \]  
\[ D_j = \frac{\sum_{i=1}^{n} t_{ij} \cdot d_{ji}}{A_j} \]

where.

\( d_{ij} \) is the travel distance between Station j to Station i; \( d_{ji} \) is the travel time between Station i and j.

Given the outbreak of COVID-19, all stations should expect changes in both L and D as most riders would reduce the number, length, and duration of trips, if possible (e.g., Beck & Hensher, 2020).

The temporary and spatial “stickiness” indices, which measure to what degree riders from Station i stick to few destinations (S\(_i\)) and few periods (S\(_p\)) and which are inspired by Simpson (1949) and Kim et al. (2017). For both S\(_i\) and S\(_p\), they can adapt the formula by Kim et al. (2017) to calculate. For instance, S\(_i\) for Station i is calculated as:

\[ S_i = \sum_{j=1}^{q} \left( \frac{t_{ij}}{A_i} \right)^2 \]  

where, q is the total number of stations (destinations) other than Station i that have non-zero trips from Station i. S has a value between 0 and 1. The larger S the fewer destinations, origins, or time slots are involved. If we talk about riders from a station, the spatial and temporal stickiness indices measure how widely distributed are their origins and how widely their arrival times can distribute across x-min time slots.

The standard deviational ellipse is used to measure the degree of concentration in the spatial pattern of origins (or destinations) of incoming trips (or outgoing trips) by station. If there are few origins toward the periphery (a spatial normal distribution), a one standard deviation ellipse will cover approximately 68% of the origins and two standard deviations will contain approximately 95% of the origins (ESRI, 2018). The larger the ellipse, the more widely across the space a station draws its incoming riders from or sending its outgoing riders to. In this study, destinations of outgoing distinct riders are chosen to produce the two-standard deviational ellipses by station, weighted by the number of distinct riders of each destination on a day. In addition, the values of the major and minor axes (A\(_{\text{max}}\) and A\(_{\text{min}}\)) of are extracted as extra variables for us to quantify and characterize the spatial patterns of those destinations. They reflect the two major directions where most origins or destinations are located. Given the above, the size of the two-standard deviational ellipses and values of A\(_{\text{max}}\) and A\(_{\text{min}}\) allow us to quantify, geovisualize and compare attractiveness of (1) metro stations amid COVID-19 and (2) of a particular metro station before and after a special COVID-19-related event.

4. Case study area

Hong Kong, a city with 7.5 million residents and 1100+ square kilometer land area is chosen as our study site (see Fig. 1).

As of 2020, Hong Kong has a metro system (called Mass Transit Railway [MTR] locally) consisting of both heavy rail and light rail. On a typical weekday pre COVID-19, MTR carries over 4 million trips, which account for about 37% of the transit trips by the local residents and visitors (Transport & Housing Bureau, 2017). Like other Asian metropolis such as Seoul, Tokyo, and Singapore, the COVID-19 pandemic
and related events’ impacts on human mobility patterns in Hong Kong can thus be encapsulated by the changes in local public transit/metro usage. Furthermore, those patterns and changes can be quantified with the measures and methods proposed above. In our empirical study, besides the quantification based on Octopus (smartcard) data on four special days, we have also assembled local traditional data such as censuses and surveys to quantify probable influencing factors of the patterns and changes. The four special days are: January 17 (Friday), 22 (Wednesday), 24 (Friday), and 29 (Wednesday), 2020. Two of the four days represent the next day right after a macro or meso-level COVID-19 related event, i.e., January 24, 2020, a day after the Wuhan/Hubei lockdown and January 29, 2020, a day after Hong Kong Government announced its “working from home” mandate. Two comparable days one week ahead of these two days were selected: January 17 and 22, 2020. The situations of these two days serve as baselines for us to fathom the impacts of the COVID-19 related event(s) on travel behaviors and patterns of local metro riders. These baselines were chosen because we assume that travel patterns of the same weekday in two consecutive weeks were the most comparable. The further the baselines went back in time, the more factors could have influenced travel patterns, e.g., New Year’s Day break, Chinese New Year celebration, seasonality, and socioeconomic changes.

Comparing the patterns/visuals of January 27 and 24 2020 (Comparison 1) allows us to detect probable impacts of the Wuhan/Hubei lockdown event on the local metro usage whereas comparing the patterns/visuals of January 22 and 29, 2020 (Comparison 2) enables us to estimate probable impacts of both the Wuhan/Hubei lockdown and the “working from home” policy events (See Fig. 2).

The two events were selected because the Wuhan/Hubei lockdown occurred remotely, and the local government did not enforce any restrictions on local travel. Therefore, if there were any changes in local travel patterns, it was voluntary behaviors of residents. In contrast, the “working from home” policy was introduced by the local government and most public servants were affected. Thus, we can see to what degree restrictions on public servants’ travel plus some subsequent voluntary residents’ reactions can affect the local travel pattern. More detail about how we operationalize the patterns/changes and their probable influencing factors is given as follows.
4.1. Patterns and changes: dependent variables

We use a matrix-based method to effectively extract information from the raw Octopus data (a few samples are shown in Table 1) on the four days for us to obtain six sets of indicators or to get ready to implement the methods mentioned above, which allow us to measure travel patterns and their changes on the four days and between two comparable days. There are multiple types of Octopus data, this study focuses on ADL, i.e., adult card only as they are more likely to be (essential) workers and have less discretion regarding whether, when, and where to ride metro. On a typical day, 90% of metro riders are also adult riders.

Specifically, we first create matrices that contain four types of information about incoming or outgoing trips by station on each of the four days and average travel distance and time of those trips (See Table 2). In those matrices, each cell’s row index (Ri) represents the origin of trips whereas column index (Cj) is the destination of the trip, for example, in the trip matrix, the value in cell (1, 2) represents the number of outgoing trips, i.e., 22, from Station 1 to Station 2.

Then we create a long table that contains the number of incoming or outgoing trips by station and by 15-min interval on each of the four days (see Table 3).

With the above matrices and tables, we then calculate the numbers of incoming and outgoing trips by metro station per hour, the average travel distance and duration of those trips, standard deviational ellipses concerning those trips’ origins or destinations, and stickiness indices measuring spatiotemporal preferences of those trips. Table 4 presents the descriptive statistics of indicators of all the 90 stations whereas Fig. 3 illustrates the standard deviational ellipse concerning outgoing trips’ destinations for Station LOHAS Park on January 24 and 17.

Table 4 shows that after the two events—the Wuhan/Hubei lockdown and Hong Kong’s Working from Home policy— the following results can be seen:

1. Fewer incoming and outgoing trips by metro station can be observed, meaning that some riders did perceive the health risk posed by COVID-19 and had reduced their trip frequencies;
2. For those continued traveling, their average travel distance seemed to be constant before and after either of the two special days whereas their average travel time slightly decreased;
3. For those continued traveling, they seemed to go to slightly fewer destinations and spread out their departure times into more 15-min intervals on a day despite that frequencies of MTR’s train services largely remained unchanged;
4. Given (1) to (3), it can also be concluded that those stopping traveling tended to have longer average travel time than those continued traveling.

Fig. 3 indicates that after the Wuhan/Hubei lockdown event, the standard deviational ellipse for 95% of the destinations of outgoing trips from Station LOHAS Park shrunk significantly. The shrinkage can be seen in the differences in the centroid, size of the ellipse, and the values and directions of both major and minor axes. Of all the metro stations, Station LOHAS Park was the one experiencing the most changes in these regards.

Table 2
Sample matrix of incoming and outgoing trips on a special day.

| Ri/Cj | 1   | 2   | ... | j   |
|-------|-----|-----|-----|-----|
| 1     | 0   | 22  | ... | ... |
| 2     | 12  | 0   | ... | ... |
| ...   | ... | ... | ... | ... |
| 1     | ... | ... | ... | ... |

Table 3
Number of incoming trips by station and by 15-min interval.

| Station ID | Time period | Number of trips |
|------------|-------------|-----------------|
| 1          | 5:30-5:45   | 110             |
| 1          | 5:45-6:00   | 200             |
| ...        | ...         | ...             |
| 1          | 0:15-0:30   | 45              |

In Fig. 4(a) to 4(d), we map out how stickiness index for outgoing trips changed between January 17 and 24 and between January 22 and 29. Fig. 4(a) and (b) show the possible impacts of the Wuhan/Hubei lockdown on the temporal and spatial index changes whereas Fig. 4(c) and (d) indicate the possible impacts of Hong Kong’s working from home policy (possibly the continuous impacts of the Wuhan/Hubei lockdown as well) on the changes. Again, the index measures whether and to what degree riders from one metro station go to few other stations or travel in few time segments.

To better geovisualize the spatial variation, we map out the index by tertiary planning unit (TPU), which is a geographic reference system demarcated by the Planning Department of the Hong Kong Government. In all the figures, blue, transparent, or red colors in each TPU represent different types of changes where blue represents negative change, transparent means little or no change, and red is positive change.

Interestingly, if we tentatively overlook the sign of the change, the TPUs that experienced the most change in the four figures resemble. This means that those TPUs were most influenced by COVID-19 related events occurring in a relatively short period (e.g., two weeks in our case) might not totally be random. It can be the same set of communities that saw the most impacts in the weeks. Furthermore, those TPUs contain one checking point, theme park, and/or terminal station tended to be consistent members of this set, e.g., West Kowloon (high-speed railway station and (checking point), Lok Ma Chau (checking point/terminal station), Lo Hu (checking point/terminal station), Disneyland (theme park), Wong Chuk Hang (Ocean Park), Tung Chung (terminal station), and LOHAS Park (terminal station). Similarly, the local central business districts (e.g., Central and Tsim Sha Tsui) also suffered significant impacts. Several other TPUs also experienced significant changes, e.g., Tai Shui Hang, Sha Tin, and Heng Fa Chuen. Without first-hand data about these polygons/communities, we have no clues to know what happened there. But one thing is certain based on Fig. 4(a)–(d): the impacts of macro- and meso-level external/internal events would not have homogeneous impacts on different TPUs.

4.2. Influencing factors of the patterns and changes: independent variables

To investigate whether and to what degree MTR riders’ travel patterns and related changes are affected by different explanatory factors, we compiled local publicly available data. The data include censuses, land use maps, and transit network files (.shp files) that can be fed into Geographic Information System. Based on these data, we formulate indicators to different explanatory factors.

In light of the literature review and local data availability, we formulate four sets of variables by TPU to measure the predictors for the change in MTR riders’ travel patterns between a special day and the
baseline. Using the TPU boundaries and attribute tables and other data available to us, we created four sets of variables:

1. socio-demographic characteristics from the 2011 Hong Kong Census Data;
2. built-environment factors depicted by the 2017 point of interest (POI) data of Hong Kong;
3. the centrality degree of each station in the MTR network based on the January 2020 Octopus (smartcard) data and MTR network shp files;
4. the changing rate of the total incoming and outgoing trips by MTR station.

Sets 1 variables are rather conventional according to the existing literature. They include all factors that can explain variations in impacts of COVID-19 and subsequent event(s) on travel patterns of metro riders. These factors include education, age, employment status, occupation, household attributes, commuting distance, and income. Existing studies have indicated, for instance, younger households would still make significantly more trips amid COVID-19 (e.g., Beck & Hensher, 2020).

Concerning Set 2 variables, six categories of POIs are separately considered: recreational, transportation, public facility, medical service, commercial, and others. The first five are singled out as we subjectively regard them as essential functions that people must turn to regardless of there exists a pandemic or not. But we are unsure what would be more important among them amid COVID-19. In addition, we use Simpson index to measure diversity of different categories of POIs. We hypothesize that diversity in a locale would reduce outgoing trips of residents therein whereas increase incoming trips of residents elsewhere. But in this study, we focus on outgoing trips only.

Set 3 variables are inspired by Zhou et al., 2019. Specifically, the average travel time based on Octopus data from an MTR station to all other stations is calculated to reflect the global centrality of that station. The shorter this time is, the higher centrality degree. Besides, the number of total population residing in 15 min’ metro ride to an MTR station are considered as an extra measurement of the regional centrality of a station. We hypothesize that lots of facilities and opportunities would be around stations with high centrality and therefore people would still need to travel to those stations despite of the outbreak of COVID-19 and increased health risk subsequently.

Set 4 variables—the rates of change in average daily trips are included because they partially reflect how incoming and outgoing metro riders by metro station perceived and reacted to the health risk of COVID-19 and related news about in the two weeks with the Wuhan/Hubei

### Table 4
Descriptive statistics of indicators (dependent variables) of all the stations.

| Date   | Incoming trips | Outgoing trips |
|--------|----------------|----------------|
|        | A (km) | L (km) | D (mins) | Sd | Sp  | P (km) | L (km) | D (mins) | Sd | Sp  |
| Jan 17 | 2296.7 (1406.3) | 7.10 (2.68) | 24.0 (4.1) | 0.048 (0.030) | 0.018 (0.002) | 2296.7 (1293.8) | 7.12 (2.66) | 23.9 (4.2) | 0.046 (0.026) | 0.019 (0.004) |
| Jan 22 | 2141.5 (1302.4) | 7.08 (2.70) | 24.2 (4.2) | 0.046 (0.026) | 0.018 (0.003) | 2141.5 (1204.4) | 7.08 (2.70) | 24.2 (4.3) | 0.045 (0.025) | 0.019 (0.003) |
| Jan 24 | 1735.7 (1026.6) | 7.08 (2.73) | 23.5 (4.3) | 0.048 (0.028) | 0.017 (0.003) | 1735.7 (964.2) | 7.10 (2.73) | 23.5 (4.2) | 0.048 (0.027) | 0.017 (0.002) |
| Jan 29 | 1048.1 (616.4) | 7.09 (2.74) | 23.5 (4.1) | 0.051 (0.035) | 0.017 (0.002) | 1048.1 (568.1) | 7.09 (2.73) | 23.3 (4.7) | 0.049 (0.026) | 0.017 (0.002) |

* Standard deviation is in the parentheses and the total number of stations is 90.
Fig. 4a. Temporal Stickiness Index ($S_p$) Change after the Wuhan/Hubei lockdown.

Fig. 4b. Spatial Stickiness Index ($S_d$) Change after the Wuhan/Hubei lockdown.
Fig. 4c. Temporal stickiness index ($S_p$) change after the working from home mandate.

Fig. 4d. Spatial stickiness index ($S_d$) change after the working from home mandate.
lockdown and “working from home” in presence as compared to the baseline we subjectively chosen: the first working week of 2020 after the New Year’s Day break and the last week when there was still little in local media about the pandemic. We hypothesize that the more sensitive riders to and from a metro station to the health risk of COVID-19 and related news the more likely that riders’ travel patterns of that station would change, e.g., fewer incoming and outgoing trips, trips staggering into more x-min intervals, and trips to fewer other stations.

Table 5 presents descriptive statistics of all the variables that we formulate.

4.3. Regression models: what affected changes in travel patterns of MTR users

Given that little has been done in the existing studies concerning what affects travel patterns in a pandemic, we assume that there exists linear relationship between travel pattern (including its changes) and explanatory factors. Our overall hypothesis is that both events would see metro riders going to fewer stations and stagger their departure times into more 15-min intervals after either of the events, i.e., at least some riders would feel higher health risks because of COVID-19 and related events and therefore adapted their travel behaviors. In terms of size and direction of the two events’ impacts, the above-mentioned four sets of independent variables would influence them. Then we adopted a two-step method (see Fig. 5) to fit a series of ordinary least square (OLS) regression models using the assembled the dependent and independent variables (see Tables 4 and 5) we assembled as input.

Our models’ results are presented in Table 6, followed by our interpretations of them. The most significant results are highlighted in bold.

Table 6 shows how the temporal and spatial stickiness index for outgoing trips changed at the metro station level is associated with different predictors at the TPU level after a macro-level and external event: The Wuhan/Hubei lockdown on January 23, 2020 and a meso-level and internal event: The Hong Kong Government’s “working from home” policy released on January 28, 2020. By definition, a reduction in the index means that metro riders from one station would go to more other stations (or travel in more x-min intervals) whereas an increase indicates that those riders would go to fewer other stations (or travel in fewer x-min intervals) (see Equation (5)).

Predictors for Wuhan/Hubei lockdown’s impacts on temporal distribution of outgoing trips by 15-min interval: Not surprisingly, the Wuhan/Hubei lockdown seemed to have enticed more outgoing riders to stagger their departure times into more 15-min intervals, where the time stickiness index changed from 0.019 on January 17 to 0.017 on January 24—a 10% change. In our regression model results, the numbers of residents in rental housing residents, the larger reduction in the stickiness index change at the 99% confidence level. The larger the number of public facilities around a metro station, the larger growth in the stickiness index changed from 0.019 on January 17 to 0.017 on January 24—

Predictors for Wuhan/Hubei lockdown’s impacts on destination distribution of outgoing trips by metro station: According to Table 4, the Wuhan/Hubei lockdown seemed to have slightly prevented a metro station’s riders from traveling to other metro stations ex post the outbreak of COVID-19. At the network level, metro riders on average went to slightly fewer destinations (mean \( S_d = 0.048 \)) on January 24 than on January 17 (mean \( S_d = 0.046 \)). In terms of predictors for the change rate in the destination stickiness index, only the number of students studying in presence as statistically significant at the 99% level. The larger the number, the larger the positive change in the \( S_d \) value, meaning that trips from a metro stations would go to fewer other stations. This indicates that many students used to travel frequently by MTR prior to the Wuhan/Hubei lockdown.

Table 5

| Variables               | Mean(Stdev)       |
|-------------------------|-------------------|
| Socio-demographics      |                   |
| Education              |                   |
| Primary and below       | 19367.42 (18131.27) |
| Secondary/Sixth Form    | 30770.21 (28804.82) |
| Post-secondary          | 15787.09 (13016.58) |
| Demographic             |                   |
| Total population        | 65924.72 (58252.43) |
| Age under 15            | 7539.12 (7101.31)  |
| Age 15-24               | 8175.94 (8422.27)  |
| Age 25-44               | 20534.33 (17653.44) |
| Age 45-64               | 20925.63 (18960.56) |
| Age over 65             | 8749.69 (7522.86)  |
| Employment              |                   |
| Age median              | 42.35 (2.50)      |
| Working population      | 33132.94 (25122.51) |
| Persons not in working population | 32791.78 (29439.06) |
| Employees               | 29669.61 (26422.38) |
| Employers               | 1376.08 (1126.73)  |
| Self-employed           | 1963.38 (1712.55)  |
| Unpaid family worker    | 123.88 (110.29)    |
| Income                  |                   |
| Median income           | 14124.11 (5841.84) |
| Monthly income under $10,000 | 13057.18 (12391.24) |
| Monthly income $10,000-$20,000 | 11268.17 (10830.95) |
| Monthly income $20,000-$40,000 | 6142.21 (5273.49) |
| Monthly income over $40,000 | 2665.39 (2490.57) |
| Occupation              |                   |
| Managers and administrators | 3100.67 (2557.91) |
| Professionals/Associate professionals | 8871.81 (7646.49) |
| Clerical support, service and sales workers | 10802.56 (10311.76) |
| Craft and related workers | 4151.92 (4655.40) |
| Elementary occupations and agricultural workers | 6205.99 (5447.83) |
| Household               |                   |
| Total households        | 22235.94 (21912.99) |
| Nuclear family households | 14968.48 (13548.32) |
| Relative households     | 3170.73 (2816.48)  |
| Other households        | 4096.73 (3196.52)  |
| Household size 1-3      | 14918.08 (12429.83) |
| Household size 4        | 4766.12 (4612.29)  |
| Household size 5 or up  | 2551.74 (2353.17)  |
| Average household size  | 2.82 (0.30)        |
| Median monthly income   | 28606.11 (21380.90) |
| Household monthly income under $10,000 | 5274.68 (5459.49) |
| Household monthly income $10,000 to $20,000 | 5304.36 (5325.44) |

(continued on next page)
Predictors for “Working from home” impacts on temporal distribution of outgoing trips by metro station: Hong Kong Government’s working from home mandate did reduce the average number of destinations that metro riders from different stations would go to, where the stickiness changed from 0.045 on January 22 to 0.048 on January 29 (see Table 4). In the regression model, the number of households with HK$40,000 or more income (i.e., local middle-class or above households) can positively predict the change rate in the destination stickiness index, meaning that the more well-to-do households living around a metro station the fewer destinations that riders from that station would visit after the mandate was enforced.

5. Discussion and conclusions

COVID-19 and related events significantly influence urban dynamics. Local travel patterns and transit demand are important proxies one can use to measure those dynamics. Amid COVID-19, changes in travel patterns and transit demand vary across locales and people. To date, the empirical information afforded by COVID-19, related events, and subsequent institutional changes and adaptive behaviors have largely been underexploited because of challenges in (a) acquiring such information prior to the availability of innovative sensors and corresponding big data and (b) deriving useful, complete, and comprehensive information from big data alone. In addition, we are still unsure what kind of measures and methods can be used to efficiently analyze those data. In this study, we hypothesize that transit riders would adapt their travel behaviors given the occurrence of macro- and meso-level COVID-19 related events. We identify and propose feasible measures and methods that can be used to quantify transit riders’ adaptive behaviors and their change amid COVID-19. Based on empirical data from Hong Kong, which consist of both big and traditional (small) data, we illustrate how these measures and methods can be operationalized and implemented. In light of the existing studies and local data availability, we also examine how those adaptive behaviors were affected by four sets of sociodemographic, built environment, metro network, and spatial factors/variables after the Wuhan/Hubei lockdown and Hong Kong’s working from home mandate, two unprecedented institutional reactions to an abrupt shock.

Based on all the above, some generic and transferable conclusions can be drawn:

First, both local and remote institutional reactions to abrupt shocks like COVID-19 can significantly influence urban dynamics, which can be measured by indicators concerning transit travel patterns across locales and people in a transit-dependent city like Hong Kong. Our above empirical studies in Hong Kong indicate that metro riders’ adaptation in departure time distribution and outgoing destination choice amid COVID-19 can be significantly predicted by sociodemographic attributes such as the percentage of residents in public housing, the numbers of students studying in different districts, workers in craft and related occupations, and well-to-do households at the metro station area level.

Ideally, people/riders should travel less often, shorten their trip distance and duration, stagger their departure times, and visit fewer destinations to reduce the health risk posed by COVID-19. But not all the people can succeed in doing so as reflected in our regression model results. For instance, in Hong Kong that wealthy households or communities tended to reduce more destinations than other households when the perceived health risk was high. Before, amid and after COVID-19, the magnitude and even sign of the impacts of sociodemographic attributes could vary. The number of students studying in different districts, workers in craft and related occupations, and well-to-do households at the metro station area level.

| Variables | Mean(stdev) |
|-----------|-------------|
| Household monthly income $20,000 to $40,000 | 6696.14 (6210.51) |
| Household monthly income $40,000+ | 4960.77 |
| Public rental housing | 19676.19 (29904.47) |
| Subsidized home | 13989.80 |
| Ownership housing | 23208.75 |
| Private permanent housing | 30318.41 |
| Non-domestic housing | 22258.68 |
| Temporary housing | 218.51 (748.08) |
| Population in domestic households | 46363.72 |
| Working from home student | 160.81 (281.56) |
| Workers work in same district | 1561.00 |
| Workers work in different district | 1230.34 |
| Students studying in same district | 27666.58 |
| Students studying in different district | 25973.93 |
| Total number of students | 10867.62 |
| Recreation facilities | 31.90 (55.96) |
| Commercial facilities | 31.90 (55.96) |
| Public facilities | 31.30 (33.51) |
| Medical facilities | 31.30 (33.51) |
| Transport facilities | 77.7 (13.08) |
| Total number of all facilities | 207.9 |
| Simpson diversity | 0.70 (0.11) |
| Average travel time to other stations | 40.11 (8.86) |
| Population within 15 min travel | 41179.85 (26804.46) |
| Incoming riders | 1.04 (0.05) |
| Outgoing riders | 1.05 (0.06) |
| Incoming riders | 0.72 (0.09) |
| Outgoing riders | 0.72 (0.08) |

Table 5 (continued)
Table 6
Stickiness index changes after remote/local events and their predictors.

| Independent variables | Socio-demographics | Dependent variable a (Time stickiness index change rate between Jan 17 and 24°) | Dependent variable b (Destination stickiness index change rate between Jan 17 and 24°) | Dependent variable c (Time stickiness index change rate between Jan 22 and 29°) | Dependent variable d (Destination stickiness index change rate between Jan 22 and 29°) |
|-----------------------|---------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
|                       | Public rental housing | −0.257 (0.008) *** | −0.189 (0.067) * |                                                                                  |                                                                                  |
|                       | Temporary housing    | 0.133 (0.148)                         |                                                                      | 0.163 (0.138)                         |                                                                                  |
|                       | Subsidized home ownership housing | −0.136 (0.447) |                                                                                  |                                                                                  |                                                                                  |
|                       | Population in non-domestic households |                                                                                  |                                                                                  |                                                                                  |                                                                                  |
|                       | Non-domestic housing |                                                                                  |                                                                                  | −0.173 (0.124)                         |                                                                                  |
|                       | Age over 65 | 0.354 (0.100)                         |                                                                      |                                                                                  |                                                                                  |
|                       | Monthly income 20-40k |                                                                                  |                                                                                  |                                                                                  |                                                                                  |
|                       | Monthly income over 40k |                                                                                  |                                                                                  |                                                                                  |                                                                                  |
|                       | Household income over 40k |                                                                                  |                                                                                  |                                                                                  |                                                                                  |
|                       | Income median | 0.138 (0.219)                         |                                                                      |                                                                                  |                                                                                  |
|                       | Craft and related occupation |                                                                                  |                                                                                  | 0.567 (0.000) *** |                                                                                  |
|                       | Students studying in different districts | 0.468 (0.009) *** |                                                                                  |                                                                                  |                                                                                  |
| Built environment     | Public facilities | 0.461 (0.000) *** |                                                                                  |                                                                                  |                                                                                  |
|                       | Medical facilities |                                                                                  |                                                                                  |                                                                                  |                                                                                  |
| Centrality degree of a station | Population within 15 min travel | 0.130 (0.162) | 0.311 (0.009) *** |                                                                                  |                                                                                  |
|                       | Average travel time to other stations |                                                                                  |                                                                                  | 0.092 (0.491)                         |                                                                                  |
|                       | Outgoing riders |                                                                                  |                                                                                  | 0.189 (0.241)                         |                                                                                  |
| Perceived health risk |                      |                                                                                  |                                                                                  |                                                                                  | 0.169 (0.072) * |

Model results

|            | F       | R²     |
|------------|---------|--------|
| Dependent variable a | 10.265 | 0.328 |
| Dependent variable b | 7.291  | 0.203 |
| Dependent variable c | 2.339  | 0.146 |
| Dependent variable d | 12.686 | 0.374 |

Notes: Standardized coefficients are in listed on the table only when the independent variables are considered in the model.

*** Indicators significance at the 99% level.

** Indicators significance at the 95% level.

* Indicators significance at the 90% level.

a Descriptive statistics of the stickiness indices on the selected dates are shown in Italic Table 4.

b Only variables selected by Automatic linear model and certified as non-collinear are listed.
factors on people's adaptation capacity. How to identify and manage all the impacts systematically become a new topic for policymakers.

Second, given the suddenness and scale of COVID-19, little has been done on how the pandemic and related events influence transit riders' travel patterns in the context where there is a high reliance on transit. In existing technical reports or guidelines on travel and transit demand modeling and transit services planning and operations, policy scenarios during and after pandemics such as COVID-19 have also rarely been considered. There is a need for us to quantify transit riders’ adaptive behaviors against the backdrop of COVID-19. Some of these behaviors might not exist prior to COVID-19, for instance, staggering trips into more time slots to avoid health risk. It is even better if we can have data concerning predictors of those behaviors. Those efforts can help us better identify vulnerable transit riders, frequent/choice transit riders, and probable transit services gaps where local transit operators can fill.

Third, both macro-level (external) and meso-level (internal) events' impacts can be measured and detected conveniently based on indicators or tools such as the numbers of incoming/outgoing trips, average distance and duration of these trips, stickiness indices of the origins or destinations of these trips, and 95% standard ellipses of the origins or destinations. Some of these indicators and tools (e.g., the 95% standard ellipses) have long been in existence but others (e.g., stickiness indices) must be invented to consider the impacts of an abrupt shock like COVID-19. It is meaningful to inventory all these indicators and tools and their respective relevance and utilities so that they better serve policy analysts and decisionmakers.

Four, in addition to those metro stations or subareas serving cross-border passengers, tourists, and exurban riders around the terminal stations, other stations and subareas can be profoundly influenced by both macro- and meso-level internal/external events. In Hong Kong, for instance, we found that Tai Shui Hang and Heng Fa Chuen can belong to the latter, where riders tended to visit fewer other stations after those events. Due to first-hand data constraints, we still do not know what happened in those stations and their adjacencies. But if we assume that mobility is a necessary condition for sufficient options and decent quality of life, then riders who had to significantly reduce the number of their destinations than others in the same city when there were COVID-19 events might suffer from fewer choices and decline in quality of life (c.f., Adey, 2017).

Despite the above progresses, our study can still be improved and enhanced in at least the following aspects. First, once there is extra financial and community support, we should conduct surveys among riders to supplement the data used in this study. The Octopus data used, for instance, only inform us where and when riders travel from and to. They do not tell us who they were, why they travelled, and how they perceived their trips. Second, due to time, data, and budgetary constraints, this study only examined impacts of two special events on metro riders’ travel patterns. In the future, impacts of more events, especially micro-level events, e.g., revealed confirmed cases and associated venues and upper customer limit for restaurants, on transit riders' travel patterns should be investigated. Finally, this study does not control adjustments of bus services when fitting the models to quantify or geovisualize impacts of different predictors on metro riders’ travel pattern changes, e.g., the stickiness index change. It also does not investigate how those adjustments might have impacted certain metro/bus riders or certain locales or metro/bus corridors more than others. In the future, more work should be done in these aspects.

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Authors statement

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