Vulnerability of Transportation Networks 2.0

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1 ABSTRACT

Public transport plays a critical role in cities by providing access and mobility. Disruptions can lead to major delays with far-reaching impacts on urban economies, security, and quality of life. Building upon prior research of transport network vulnerabilities in New York City, the differences in impact between single node disruptions and simultaneous paired disruptions across five global cities of varying network size and structure would uncover synergistic effects of node-disruption that indicate a connection with the size and structure of the networks studied.

The resulting methods and findings offer urban planners and security analysts a quantitative framework through which to measure such synergistic effects and use them to improve existing public transport systems. We hope that the breadth of this research can be expanded to include additional urban areas, and future findings may result in an understanding of universal synergistic patterns of node-disruption effects across scale and structure of urban transportation networks.

2 INTRODUCTION

Subway systems form the backbone of urban transportation in many cities, ensuring the smooth functioning of daily activities. Within this importance, however, lie vulnerabilities; the scale and limitations of such transport networks leave them prone to disruptions, whether due to technical difficulties, natural disaster, or deliberate tampering. Hence, to minimize repercussions, it is essential for cities anticipate, plan for, and ideally hedge against such effects. Due to the inherent networked structure of these systems, repercussions of a station failure can have impacts throughout the entire network. While single node failure in rapid transit systems has received considerable attention [Jenelius and Mattsson, 2015, Li and Ozbay, 2012], studies involving failure in multiple nodes have been relatively unexplored. M'cleod et al. [2017] examine the cumulative impact of simultaneous failure in multiple nodes in the New York City subway system. They highlighted the idea of synergistic effects, revealing that the combined impact of simultaneous disruptions on two nodes may have more extensive impacts than the cumulative disruption, a 'greater-than-the-sum-of-the-parts' phenomenon. This study builds upon their research by extending these methods of synergistic analysis to 4 major global cities, further investigating these effects across cities of varying size and structure.

The topic of subway network disruption has been relatively well explored [Han and Liu, 2009, Sun et al., 2015, Kim et al., 2015, Yin et al., 2016]; in their analysis on Beijing's subway system, Han and Liu [2009] found that networks are largely resilient to the random loss of nodes but are vulnerable to attacks on high-degree hubs. This is supported by Yin et al. [2016] and Sun et al. [2015], both of whom found that subways systems are robust to random disruptions but more vulnerable to intentional nodal-based disruptions. They suggest that certain combinations of nodal disruptions may have larger impact on the network. This finding supports our research objective to uncover the synergistic effects of simultaneous disruption compared to single-node disruption. Kim et al. [2015] highlight that hubs may not be the most important nodes in the network. In contrast to traditional notions of network vulnerability, Kim suggests that non-transfer stations with high passenger flows or bridge stations to hubs may be more critical. Existing studies have identified important patterns in network vulnerability, but are mainly focused on one network. Our study aims to contribute to existing research by analyzing network vulnerability of multiple cities, comparing the impacts between cities through a topological and geometric perspective [Derrible and Kennedy, 2009] to uncover any patterns and universalities between subway systems worldwide.

Multiple studies have analyzed subway systems as complex networks and found that they exhibit both scale-free and small-world features [Latora and Marchiori, 2002, Roth et al., 2012]. Looking at subway systems as complex networks provides a holistic view of the system; this paper adopts these practices to analyze the properties and effects of network characteristics and ridership of 5 subway systems in the world to uncover the effects of disruptive activity on the network. This paper will (1) briefly present the data sources and exploratory data analysis, (2) present the methodology to construct each network and introduce the concept of synergy, and (3) analyze the differences in impact between single node and simultaneous two-node disruption, to identify any universalities between networks.

3 DATA

3.1 Data sources

Data was collected from 4 major cities: London, Singapore, Taipei and Washington, DC, in addition to data gathered from M'cleod et al. [2017] for New York City. The temporal granularity of passenger origin-destination travel data differs between cities due to data availability (Table 1), 5 percent of all Oyster card journeys in a week during November 2009 were collected for London, while one week of ridership data was taken for all other cities. Nevertheless, these 5 cities provide a representation of cities across Asia, Europe and North America with varying sizes and structures, making them particularly useful to test if universalities exist across a wide-range of subway networks. Information on station locations, schedules, and individual passenger entrance and exit smartcard data were collected for each city, and a directed weighted subway network was constructed.

3.2 Exploratory Data Analysis

We conducted exploratory analysis to understand passenger flows across each of the cities in our study. Derrible and Kennedy [2009] found that most subway systems exhibit scale-free and small-world structure.

Scale-free networks arise from the preferential attachment of new vertices to already highly connected sites, and can be interpreted by power law distributions in node linkages (Figure S4). These patterns and properties have been found to have an impact of ridership, and imply that certain nodes handle volumes orders of magnitude (i.e. *exponentially*) greater than others Derrible [2012]. Further, scale-free properties impact the disruptive nature of these networks; scale-free networks tend to be robust against accidental failure, but vulnerable to coordinated attacks Barabasi and Albert [2011]. Scale-free networks also exhibit small-world features in which nodes tend to have a significantly smaller average shortest paths than would be exhibited in a random network.

Table 2 is sorted by the the total size of the networks from the largest to smallest. The activity standard deviation from log-norm fit decreases with the size of the network, suggesting that commuters in smaller cities or less complex networks are more likely to utilize a few key stations in the network. In addition, passenger activity by station during the AM peak on weekdays was visualized across the entire network for each city. Figure 1 shows a clear home-to-work flow in London and Taipei, while passenger flow in Singapore and Washington, DC appear to be more evenly distributed across the network. This reveals that travel pattern is different between cities across the world.

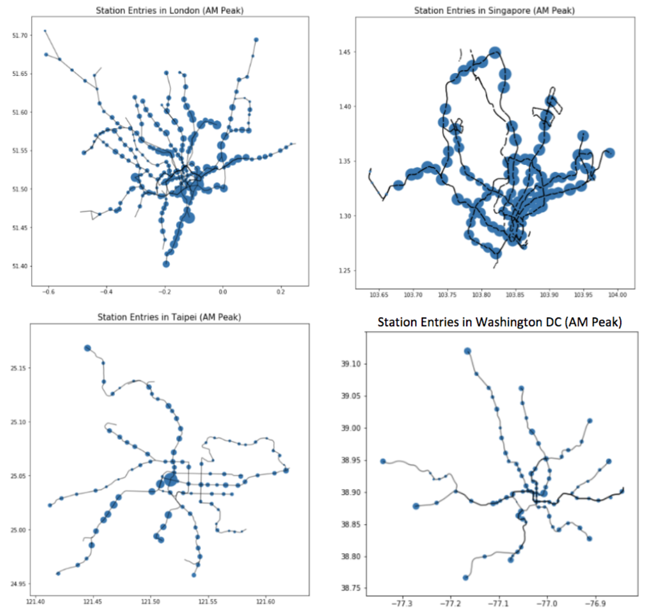

Figure 1. Passenger Activity across all stations in all cities reveal underlying travel pattern during AM Peak on weekdays.

4 METHODOLOGY

Our research methods can be divided into 2 major components; first, modeling the subway system as a directed weighted network; second, assessing the criticality of single-node and paired-node disruptions, examining the synergistic effects to provide a comprehensive understanding of network vulnerability. Physical station locations and schedule are used to construct the network from a geographic and temporal perspective. Stations are taken as master nodes, and stations along each line are taken as subnodes. Master nodes and subnodes are connected by wait time and exit time, while subnodes within the same station are connected by transfer walk time (the time to walk line to line).

Upon construction of the networks, we observe that subway systems across the world have differing structures and varying levels of complexity (Table 1), making it all the more important to provide a quantitative method of cross-comparison to facilitate understanding of the impact that such complexity measures have on the synergistic effects observed in each network.

4.1 Criticality and Synergistic Effects

After constructing the network, data from passenger origin-destination flow were combined to compute travel time and delay on each subway journey from node to node using the Dijkstra algorithm for shortest network path measurement,

	Population (mil)	Land Area (mi²)	Total Ridership	Masternodes	Subnodes	Edges	Degree
New York City	8.53	469	2820027	465	913	5749	4.17
London	8.14	607	577053	270	390	2274	3.45
Singapore	5.61	278	12872584	118	177	835	2.83
Taipei	2.71	104	1084716	106	167	759	2.78
Washington, DC	0.69	68.34	8795116	91	141	694	2.99

Table 1. Basic properties of network for each city, ranked by scale and complexity of the network. New York City is the largest network with the largest number of nodes and highest degree while Washington, DC is the smallest network in this study.

	Activity_Slope	Slope_Std	Activity_Intercept_Std	Activity_Mean	Activity_Std
NYC	-0.4	0.09	0.04	8.27	1.04
London	-0.39	0.06	0.03	7.94	0.97
Singapore	-0.2	0.03	0.01	10.93	0.99
Taipei	-0.61	0.08	0.03	10.81	0.82
Washington DC	-0.36	0.06	0.03	11.3	0.59

Table 2. Power law and log norm fit of activity in each of the cities studied

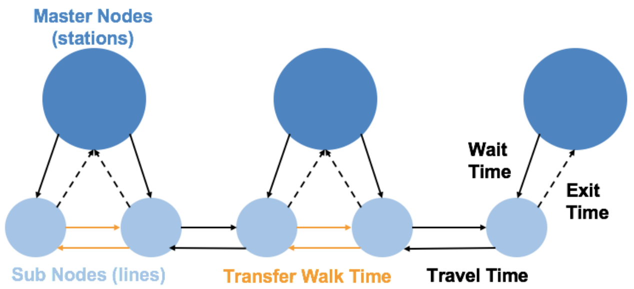

Figure 2. Network structure; master nodes and subnodes connected by edges (transfer time, travel time, wait time and exit time).

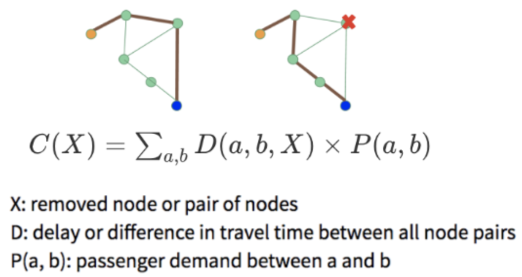

Figure 3. Criticality scores are computed by simulating single station disruption, and the new route under disruption. Criticality scores of each node or pairs of nodes are computed by taking the sum of lost "Passenger Hours" under travel disruption.

under the assumption that commuters display both perfectly rationality and have perfect information regarding the fastest route from origin to destination (while not true for all passengers, this assumption has become increasingly prevalent in an age of routing apps, and serves as a rough approximation). Travel disruption was simulated by rerunning the Dijkstra algorithm multiple times while removing nodes. The extent of the impact was measured through the amount of "Passenger Hours" lost when any one node or set of nodes are removed. "Passenger Hours" can be defined as the total time lost as a result of a network disruption, measured as the product of the number of passengers traveling on that route, and the delay in travel time. If the disruption generates broken paths, the delay is set to 60 minutes because this is a temporary disruptions and passengers would find alternative services, such as buses, taxis or ride-share, to complete their trips.

The synergistic effects of simultaneous paired disruptions can be assessed by comparing the extent in which the criticality scores of paired disruptions differ from the sum of separate disruption on single nodes.

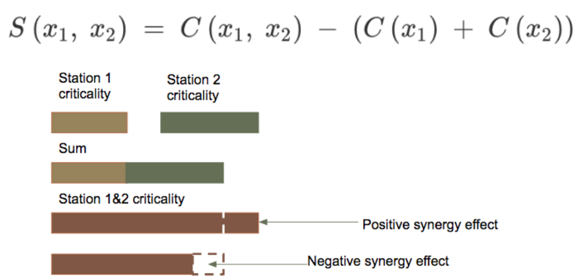

Figure 4. Positive and negative synergistic effects are measured by comparing the criticality scores of paired disruptions and the sum of 2 separate single node disruption

In our study, we are interested in identifying stations with positive synergies, in which simultaneously paired disruptions have higher impact on the network compared to separate disruption on single nodes. This is the 'greater-than-the-sum-of-the-parts' effect which will be of particular interest to urban planners and security analysts.

5 RESULTS

5.1 Single node disruption

Results from the single-node disruption reveal that transfer stations serving more than one line are most commonly stations with the highest criticality scores, as they provide connectivity for commuters moving within the network. In addition, stations with high commuter volumes also have high criticality scores. However, while London, Taipei and Washington D.C. reflect a similar trend in which the highest criticality scores are observed downtown in the city center, Singapore has a relatively different pattern. The highest criticality scores are observed in transfer stations to the west and northeastern parts of the island which serve key centers for industrial and residential activities. The relatively even distribution of criticality scores across the network may be attributed to the underlying distribution of the population and the planning policies guiding land use in Singapore, and its unique position as a city-state.

5.2 Pair Node Disruption

Pair-node disruptions were simulated for all 5 cities. However, due to constraints in computational time, the pair-node disruption was measured for all pairs of stations in smaller networks (Singapore, Taipei and Washington, DC), and only the top 50 pairs of stations in larger networks (London and New York City). Nevertheless, positive synergies was observed in all 5 cities. Positive synergies occur when disruption on a pair of stations simultaneously exceeds the cumulative impact of disruption on two stations separately. The percentage of station pairs with positive synergies among all pairs increases with the size of the city. Interestingly, despite only considering only the top 50 stations, the percentage of positive synergies observed in larger networks such as London and New York City exceeds that in smaller networks.

5.3 Synergies Explained

To explain the occurrence of synergies in the network, we examine both global and local patterns. First, we find that synergies are closely related to overall network complexity. Figure 5 a shows that the percentage of positive synergies increases as the number of edges in log scale increases, though with the notable exception of Singapore, which has the highest percentage of positive synergies despite it being a smaller network. The presence of Singapore as an outlier may be due to the relatively higher volume of ridership, as seen in Figure 5 b where the percentage of positive synergies is observed to increase with ridership. This suggests that while synergies can be explained by complexity to a certain extent, other factors may be additionally important.

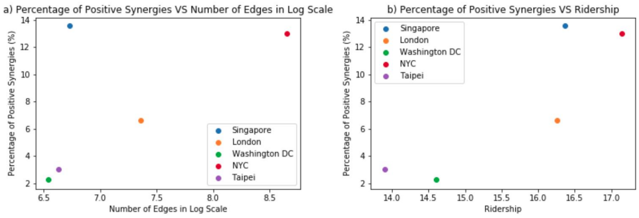

Figure 5. a) Percentage of positive synergies largely increase with the complexity of the network, with except Singapore which is an outlier, this may be due to the high ridership volume in Singapore. b) Percentage of positive synergies largely increase with ridership

Second, we find that, upon pair-node disruption, the percentage of relative synergies is related to the distance between the two stops. Station pairs with near-zero relative synergies are found between stations of any distance, while pairs with negative synergies are largely only found between stations less than 10 stops apart with the exception of Taipei. Interestingly, station pairs with exceptionally high positive synergies also only occur where distance is less than 10 stops.

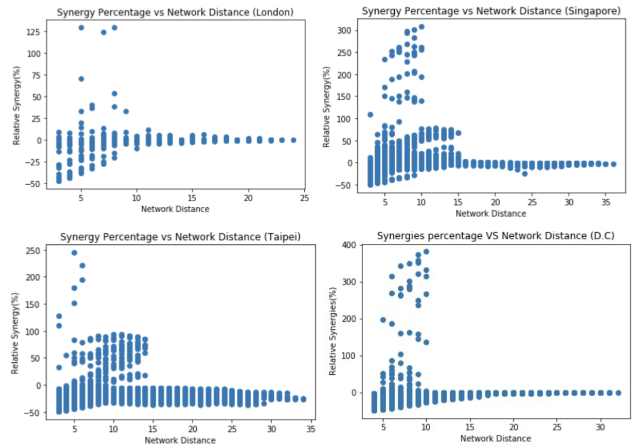

Figure 6. Percentage of relative synergies in relation to network distance in stops

Lastly, synergistic effects can perhaps best be explained through the lens of betweenness centrality. Betweenness centrality is based on the idea that a node is more central if it is traversed by a larger number of the shortest paths connecting nodes in the network. To encompass the demands of our question, we introduce a new measure of network distance: relative betweenness. Relative betweenness of two nodes refers to the relative size of an overlap in the sets of shortest paths, calculated as:

$$RB\left(x_1,x_2\right)\ = B\left(x_1\right)+B\left(x_2\right)\ - B\left(x_1|\,x_2\right) \quad (1)$$

where RB is Relative Betweenness and B is Betweenness

Relative Synergies are computed as:

$$RS = \frac{S(x_1,x_2)}{C(x_1)+C(x_2)} \quad (2)$$

where RS is Relative Synergies

In Figure 7, we examine the relative betweenness against the relative synergies for each city. A large cluster of near-zero relative synergies can be observed in all cities, as can clear clusters of highly positive and negative synergies. There appears to be a negative relationship between relative betweenness and relative synergies, with relative betweenness decreasing as relative synergies increases. The relationship is strongest in Washington, DC with a correlation coefficient of -0.88, and fairly weak in Singapore and Taipei; this may be due to the presence of outliers in these cities, having a few stations with exceptionally high relative synergies. This suggests that topology of the network is almost certain to be an important factor in explaining synergistic effects.

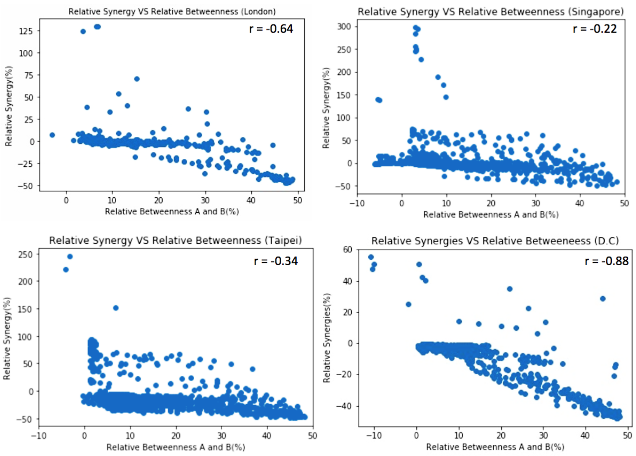

Figure 7. Relative betweenness against relative synergies for stations with top 50 criticality scores; a clear cluster of stations is observed at zero and negative synergies, with few stations with exceptionally high positive synergies in all cities.

A comparison between weekday and weekend travel disruption reveals that temporal variations have little effect on the occurrence of positive synergies in the networks studied. This implies that synergistic effects likely result more-so from topological characteristics than from variations in travel demand.

In an attempt to uncover where such positive synergies occur, we conducted an analysis for the Washington, DC network, taking a closer look at both broken-path and delay-path differences. To accomplish this, we define the betweenness as:

$$B(x) = P_{delayed}(x) + P_{broken}(x) \quad (3)$$

where $P_{delayed}$ is number of delayed paths and P_{broken} is number of broken paths.

Using this formulation, we can then define broken-paths and delay-path differences as:

$$D_{droken} = P_{broken}(x_1) + P_{broken}(x_2) - P_{broken}(x_1|x_2) \quad (4)$$

$$D_{delayed} = P_{delayed}(x_1) + P_{delayed}(x_2) - P_{delayed}(x_1|x_2) \quad (5)$$

where D_{broken} is broken path difference, $D_{delayed}$ is delay path difference.

The Figure 8 shows relationship between broken-path and delay-path differences, revealing that for station pairs with relative synergies higher than 150% (i.e. when synergistic effects exceed 1.5 times the combined criticalities for the respective nodes), the number of broken-path differences is negative; the number of delay-path differences is positive. This suggests that the initial single node disruption is converted to a broken-path, resulting in more significant impacts.

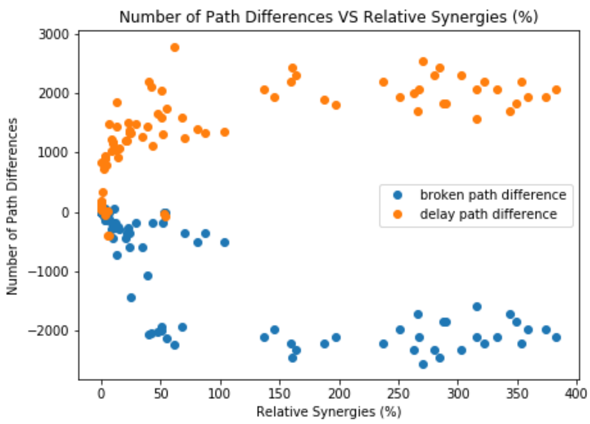

Figure 8. The only positive synergies pair of Washington D.C and it shows higher percentage of relative synergies has negative number of broken path difference and positive number of delayed path difference

To demonstrate, Figure 9, shows that where a single-node disruption generates only a delayed path, simultaneous paired-node disruptions result in broken paths, bearing a significantly greater impact on the throughput of the system.

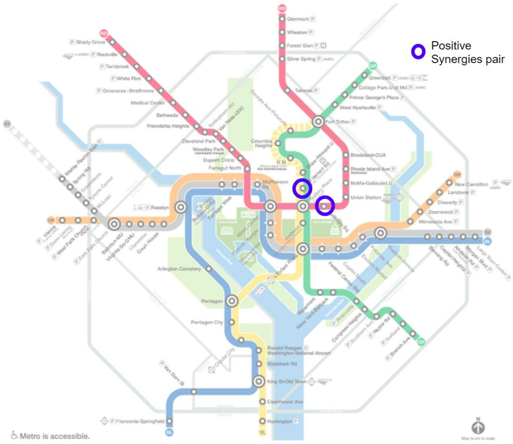

Figure 9. Station pair with the highest number of positive synergies, exemplifying the scenario where the largest number of broken-paths is generated

6 CONCLUSIONS

Our study of disruption effects in the transportation networks of five global cities provides insight into the nature of scaling and structure of subway systems across the globe with a focus on synergies produced by multi-nodal network disruptions. We uncover synergies to reveal unique effects, differing considerably from the sum of the pairs, and lay the groundwork for further research into the universalities that certain transportation structure may contain.

These insights, alongside the methodology used here, can provide urban planners and security agents with a quantitative framework through which to better design, expand, and protect urban areas. They can also be used by city agencies to prioritize maintenance and provide bolstered support during large events or in emergence situations.

Origin-destination data is a critical factor in the construction of such networks, and is essential to conduct analysis. While many cities collect such data, others do not, or only collect portions of the total requirement. The development of a model for predicting flows may be used to estimate such flows, thus enabling approximate analysis in cities lacking such data. To provide a more rigorous analysis of what specific elements of scale and structure effect the synergistic nature of these disruptions, more data and further study is needed. However, we feel that the methodology and approach outlined above lays a strong foundation for future work.

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SUPPLEMENTARY MATERIAL

1 DATA SOURCES

1.1 London

Data is readily available from the London Data Store, broad data on station entry and exit for weekday and weekends can be used to identify general travel patterns in the city. More granular data from the Oyster card containing individual entry and exit in the London Underground may be accessed. While the data available includes 5 percent of commute in November 2009, the granularity of the data will be useful to better model travel demand. Station locations are available via a geocoded KML, and schedule information can be extracted from the Transport for London live feed.

1.2 Singapore

Data containing commuter travel data is recorded through the ez-link card. This dataset is not openly available, but may be obtained directly from the Land Transport Authority. Access was granted for 2 weeks of data in January 2018, one for a randomly selected week, and another for a week coinciding with a public holiday. Station locations are available in the form of json and shapefile, and schedule information can also be extracted from a live feed available from the SMRT Connect App.

1.3 Taipei

Data containing commuter travel data is recorded through the easycard, a contactless travel card on the MRT network. The dataset is openly available from Data.Taipei, containing origin-destination passenger flows and counts for each hour of the day. The records for the month of February 2017 will be used. Station locations are available in the form of a shapefile

1.4 Washington, D.C

Data for Washington, D.C. was collected from two primary sources, a publicly available dataset on PlanItMetro, showing the average origin-destination flows in a month. To acquire structural data for the Washington D.C. Metro, we used the Washington Metropolitan Area Transit Authority (WMATA) API, compiling station location, line structure, and distance metrics into a central dataframe to be combined with the passenger-flow data, which provides the weightings to the network structure.

1.5 New York City

Data was collected from the work done by the previous capstone team.

2 TECHNICAL DESCRIPTION OF DATA CLEANING

The bulk of the data cleaning process was dedicated to preparing the data for network construction

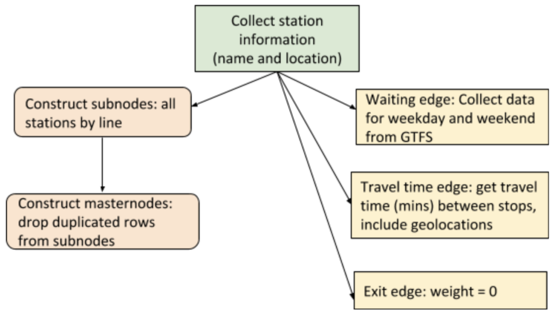

Figure S1. Workflow for data cleaning for network construction; including nodes and edges

Figure S1 shows the workflow for data cleaning to construct the network for each city. After getting the data ready for network construction, the package Networkx was used to construct the network, connecting the nodes and edges and weighting them by travel time and waiting time.

3 IMPLEMENTATION OF METHODOLOGY AND COMPUTATIONAL DETAILS

Network disruption for single and paired nodes was simulated for all cities. Criticality scores was computed for all stations under single node disruption. For paired node disruption, due to the large network scale for New York and London, station pairs were selected from stations with top 50 criticality scores. Paired node disruption was simulated for all pairs of stations for all other cities (Singapore, Taipei and Washington, DC). The simulation of paired node disruption was computationally intensive with runtimes ranging between 2 to 5 hours. Network disruption was simulated for all cities for both weekday and weekend schedules to identify any differences in network vulnerability across the day of week. Passenger origin destination data between the morning peak (5am to 10am) is taken for weekday disruption, while data for midday (11am to 3pm) is taken for weekend analysis. This time periods was selected for two reasons. First due to limitations in data availability, constrained by the data available from Washington, DC. And second, midday was selected for weekends, as we assume that peak travel is more likely to occur during that period compared to morning rush hours.

4 DETAILED ANALYSIS

4.1 Passenger Flow:

We conducted exploratory analysis using the origin-destination travel data to better understand the travel patterns in each city. The individual level data was aggregated to reflect the number of people entering and exiting each station during the morning (AM peak) and evening (PM peak) rush hours. Again, AM peak is defined as time between 5am to

10am and PM peak is defined as between 3pm and 7pm. As an example, we present two cities for comparison here.

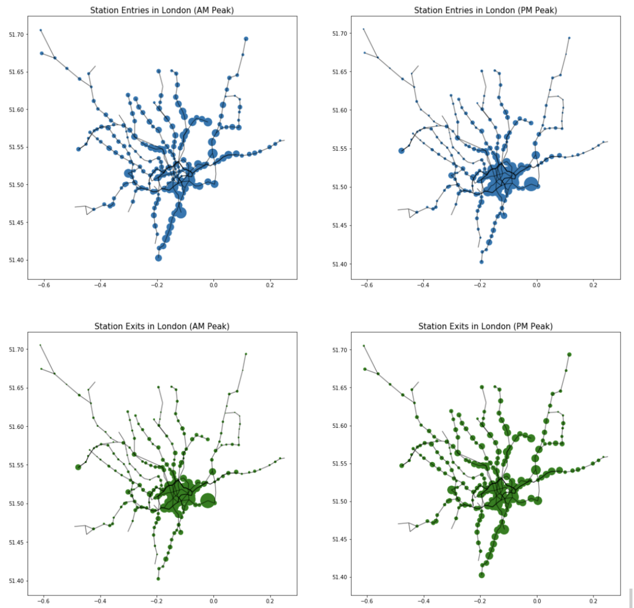

Figure S2. Passenger flow in London underground during AM and PM peak.

Figure S2 presents the passenger flow in the London underground. During the AM peak, a clear even pattern of commuter entries across the whole network can be observed. In the AM peak, we find that most commuters are exiting in Central London, and a symmetrical pattern can be observed during the PM peak where large volumes of commuters are entering the same stations. This pattern reflects a possible home-to-work flow.

In comparison, a different pattern is observed in Taipei (Figure S3). While a relatively even pattern of commuter entries was observed across the subway network during the AM peak, and majority of commuters are exiting the stations along the Tamsui-Xinyi line and stations in downtown Taipei near the Zhongzheng District, the PM peak shows a very different pattern. Relatively large volumes of commuters are entering and exiting stations on multiple lines across the city, but the highest volumes are observed near the Zhongzheng District and Tamsui station, a popular seaside district. This indicates differences in lifestyle habits between different cities. While a clear home-to-work flow can be observed in London, city dwellers in Taipei prefer to unwind by heading downtown after work.

4.2 Power Law of Passenger Flow:

Similar to other emergent phenomenon, we expect passenger flows to follow a delineation of power-law scaling, with majority of passenger volume concentrated at a few hub stations and quickly trailing off among the majority of others. We take

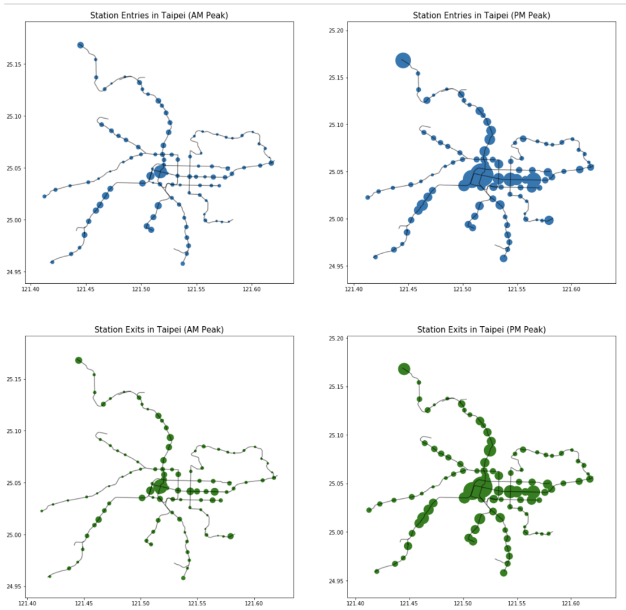

Figure S3. Passenger flow in Taipei during AM and PM peak

the passenger flows from each of the five cities, and compare them by taking a linear regression with logarithmic transformation. The results reveal that passenger flow at the top 20 stations in all cities largely, though not perfectly (as can be expected of top-down man-made systems), follow power law scaling patterns (Figure S4), suggesting that the networks can indeed be classified and analyzed as if scale-free.

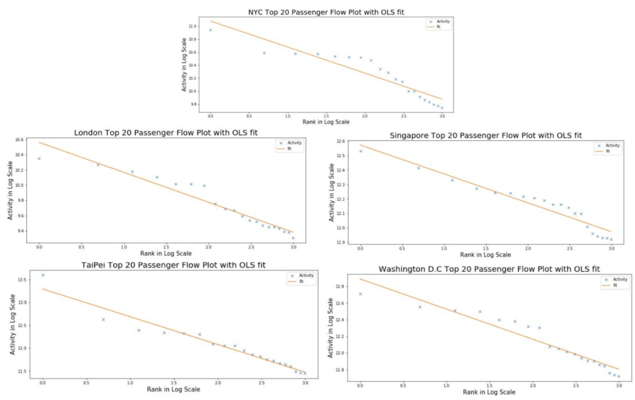

Figure S4. Stations with top 20 passenger flow fitted with linear regression with logarithmic transformation, showing that passenger flow in most cities largely follow the power law.

The passenger flows in each city were log-normalized and the distributions of activity were visualized (Figure S5). With the notable exception of Singapore, they display Gaussian trends, implying that for most cities there are few stations with exceptionally high or low activity; rather most stations experience an average volume of passenger flow. While we anticipate the exception of Singapore to be in some ways due to the geographic constraints on expansion and/or the strong role of central planning in the nation-state, this anomaly warrants further study before any conclusions can be drawn.

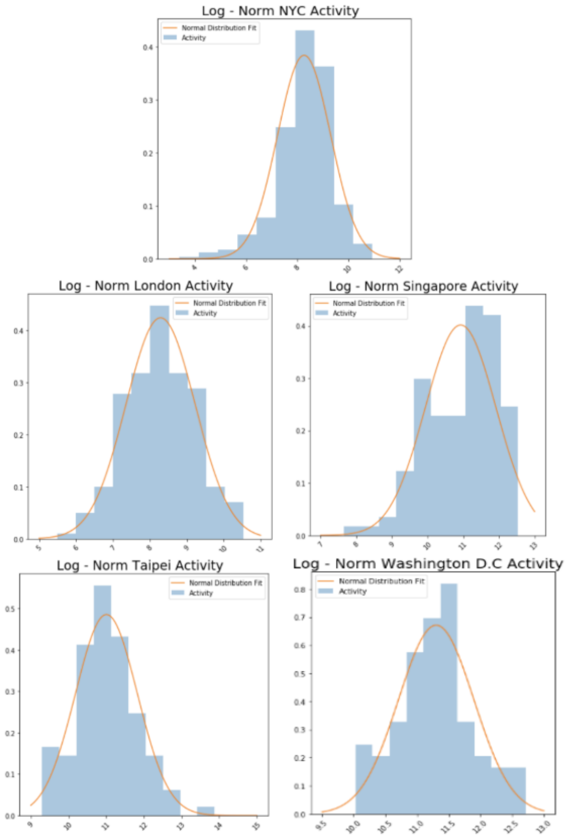

Figure S5. Station activity in all stations largely follow a log-normal distribution with the exception of Singapore where the distribution is skewed to the right, suggesting that the proportion of stations experiencing high passenger flows is higher than other cities.

4.3 Single Node Disruption:

The London network (Figure S6) comprises 270 master nodes and 390 sub nodes. There are total 660 nodes and 2274 edges. The average in and out degree is 3.4455. It is by far the most complex network in our study. It is observed (Figure S7) that major transfer hubs such as King's Cross St.Pancras, Euston, and London Bridge located at Central London are identified with the highest single node criticality score, this can be attributed to the high passenger activity in these stations. High criticality score is also observed for intersection on the route to outer London, such as Stockwell and Finsbury Park, since the disruption of those stations will affect all the stations beyond them on the route to outer London.

Figure S6. Constructed London Network

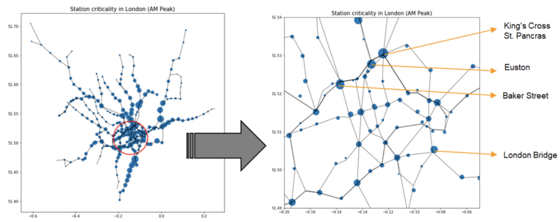

Figure S7. Criticality scores by station in London

The Singapore network comprises 118 master nodes and 177 subnodes. As a relatively complex network, there are a total of 295 nodes and 835 edges. The completed network shows all the subnodes connected by transfer edges and edges travelled by trains (Figure S8).

Figure S8. Constructed Singapore Network

Figure S9 shows the criticality scores by station in Singapore. Criticality scores are highest at key junctions such as

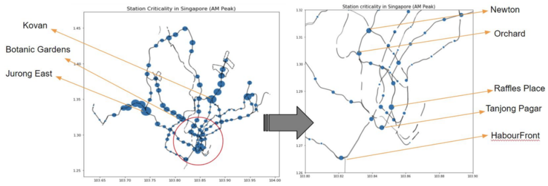

Figure S9. Criticality scores by station in Singapore

Jurong East, Botanic Gardens and Kovan, where more than one line intersect. In the central business district in downtown Singapore, the highest criticality scores are again observed in key transfer stations, Raffles Place and Newton, as well as Orchard and Tanjong Pagar where there are high commuter volumes. We observe that stations with the highest criticality scores are situated at the western and northeastern part of the network. And while Jurong East, Serangoon and Lakeside have very high passenger volumes and high criticality scores, Kovan and Chinese Garden have comparatively lower passenger volumes but similarly high criticality scores. This observation is similar to that highlighted by (Kim 2015) in his study on Washington, where he highlighted that non-transfer stations with high passenger flow volumes and bridge stations may be more critical.

The Taipei network comprises 106 master nodes and 167 subnodes. With a land area smaller than that of Singapore, it has a relatively wide coverage, with a total of 273 nodes and 759 edges (Figure S10).

Figure S10. Constructed Taipei Network

Figure S11 shows the criticality scores by station in Taipei. Similar to the other cities, the stations with the highest criticality scores are mainly those at key junctions serving more than one line of service. Other stations with relatively higher criticality scores are those with high commuter volumes. Notably,

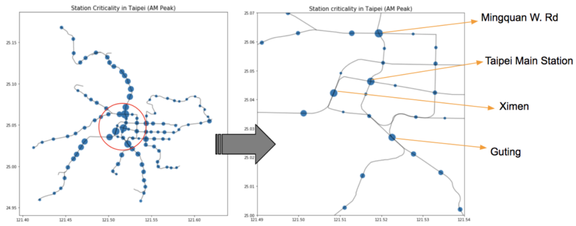

Figure S11. Criticality scores by station in Taipei

Mingquan W. Rd station has the highest criticality score despite having lower passenger volume compared to Taipei Main Station and Ximen station. This may be because Mingquan W. Rd station provides key connectivity on the Tamsui-Xinyi line, allowing for transfer opportunities to other parts of the city.

The Washington D.C. network is the smallest with 233 nodes and 696 edges. Despite it being much smaller in scale compared to London, it demonstrates very similar patterns previously in terms of commuter home-to-work travel flows. The highest criticality scores are observed in station downtown, where most people are exiting during the AM peak, signaling the role of these stations as gateway to work opportunities. Similar to Taipei, Gallery Place-Chinatown (in DC) has the highest criticality score and all stations are transfer node except Farragut North station. The interesting stations is Rosslyn, which has very low passenger activities, but it has very high number of critical score. The reason why Rosslyn has higher score is it's a junction station that connect two out-skirt lines to downtown D.C. (Figure S12).

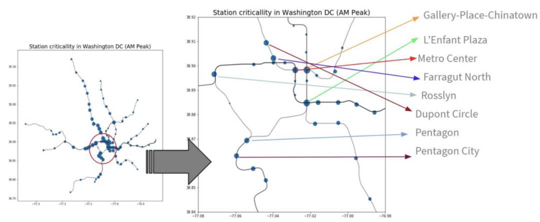

Figure S12. Criticality scores by station in Washington, DC

We believe that the methodology and findings above serve as a strong foundation for future research. While more insight and data is needed to truly determine universalities in synergistic disruptions of urban transportation networks, we hope this serves as a framework that is useful to the planning and security communities, in addition to future research.