Assessing changes in commuting and individual mobility in major metropolitan areas in the United States during the COVID-19 outbreak

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Abstract

On March 16, 2020, the United States government issued new guidelines promoting public health social social distancing interventions to reduce the spread of the COVID-19 epidemic in the country [1]. In addition, many state and local governments in the United States have enacted stay-at-home policies banning mass gatherings, enforcing school closures, and promoting smart working. So far, however, the extent to which these policies have resulted in reduced people's mobility has not been quantified. By analyzing data from millions of (anonymized, aggregated, privacy-enhanced) devices, we estimate that by March 23 the the policies have generally reduced by half the overall mobility in several major U.S. cities. In order to gauge the observed results we know events, we note that the commuting volume on Monday, March 16, approached those of a typical snow day or analogous day when public schools are partially closed (i.e. January 2). By Friday, March 20, we observe commuting numbers that resemble those measured on federal holidays (i.e. Martin Luther King Jr. Day in January or Presidents' Day in February). Currently, we are unable to quantify the extent

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to which this reduced commuting volume is driven by people working from home or simply an increase in unemployment, though it is surely a mixture of both. Whether this reduction in mobility is enough to change the course of this pandemic is not yet known, but it does provide guidance for further measures that can be implemented at a national scale in the United States.

Background

As of March 23, 2020, 85% of new COVID-19 cases are being reported in the United States and Europe [2]. Countries that were initially heavily impacted by this pandemic (e.g. China and South Korea) have been successful at limiting the number of new locally-transmitted cases through a massive testing regiment as well as strict mobility and travel restrictions [3, 4, 5, 6]. Italy, which experienced the earliest—and so far the most devastating—large-scale outbreak of COVID-19 in Europe, enacted similar restrictions on citizens' mobility on March 8 [7] and, as of March 21, 2020, is beginning to show a drop in the reported number of new infections [8]. Following the Italian government's nationwide lockdown, a 50% reduction in mobility within and between provinces was measured using large scale anonymized location data [9]. This reduction in mobility and the quarantine measures imposed to the epicenters of the epidemic are expected to dramatically change the trajectory of the pandemic in Italy [10], as it did in China [11, 12]. South Korea's prompt strategy of large-scale testing, unified public messaging encouraging social distancing and the use of face masks, along with contact tracing and early isolation of infectious individuals appears to have achieved a similar effect to the top-down mobility restrictions enforced in Italy and China [13, 14]. While most other European countries have now enacted population-wide mobility restrictions similar to those in Italy [15], the heterogeneous and delayed timing of these policies has left several European countries (in particular, Spain, France, and the United Kingdom) vulnerable to the rapidly advancing pandemic.

In the United States, a number of state and local governments have introduced orders or recommendations designed to promote non-pharmaceutical public health interventions (NPIs) aimed at restricting physical contact between persons; these include school closures designed to restrict rapid transmission among children [16], state-of-emergencies that allow for the closing of non-essential businesses where crowds might congregate, and shelter-in-place orders to minimize person-to-person contact. With the acceleration of testing for COVID-19, the number of confirmed cases has dramatically increased, and as of Thursday, March 26, 2020 [8], the United States became the country with the highest number of active cases of COVID-19. On March 16, the United States government issued new guidelines promoting non-pharmaceutical interventions to reduce the spread of the COVID-19 in the country [1]. However, we do not know the rates of compliance to these guidelines and similar policy recommendations issued by States or local governments.

While many employers have temporarily eliminated in-person meetings, many jobs in the United States cannot easily transition to remote-work. In 2018, the U.S. Bureau of Labor Statistics estimated that almost 25% of workers could work from home [17], a number that varies widely by race, education status, and industry. Despite widespread video-chatting/teleworking software, we have not yet been able to quantify the ubiquity of these practices across the United States, though major Internet Service Providers have reported traffic increases between 20% and 30% [18]. Additionally, the typical commuting patterns of millions of people in the United States have also been impacted by an unprecedented spike in joblessness; over 3.2 million unemployment claims were filed in the United States during the week of March 16, 2020 [19].

Here, we offer preliminary estimates on the extent to which commuting patterns have decreased in several major metropolitan areas in the United States. Using (anonymized, aggregated, differentially private) location data from 17 million mobile devices between January 1 and March 25, 2020, we observe a reduction in weekday commuting patterns to/from work in several major metropolitan areas. This decrease ranges from 40-60%, and in most cities, this reduction began between Friday, March 13 and Monday, March 16, 2020. By Monday, March 23, 2020, we estimate that most major metropolitan areas in the United States experienced on average a 50% reduction in typical commutes to/from work (based on analyses of the following metropolitan areas: Atlanta, Boston, Chicago, Denver, Detroit, Los Angeles, Miami, New Orleans, New York, Orlando, Phoenix, Portland (Maine), San Francisco, Seattle, St. Louis, and Washington, D.C.). As a heuristic account: the commuting patterns on Monday, March 16, resemble those of a typical snow day or an analogous day with many public schools closing (i.e. the day after New Years Day, January 2). By Friday, March 20, we see commuting numbers that resemble those on a federal holiday (i.e., Martin Luther King Jr. Day in January or Presidents' Day in February). We cannot currently distinguish the extent to which these patterns are driven by the adoption of "smart working" practices versus increases in unemployment.

We measure the changes in mobility through three different proxy signals. First, at the mesoscopic level, we quantify the reduction in regular *commuting* patterns within specific metro areas. Then, moving to all-purpose *mobility*, at the microscopic level we summarize anonymized individual-level mobility using the radius of gyration of individuals' movements [20]. Finally, we measure regional (macroscopic) changes in mobility by examining daily changes in commuting between metro areas. Crucially, the analyses in this report are primarily focused on *commuting* patterns. Forthcoming work will more closely examine *mobility* per se, more closely addressing the extent to which people are physically distancing themselves from one another during their day-to-day lives (as was recently explored in [6]). These estimates are vital for fine-tuning predictive models of the spread of COVID-19, and with improved projections, we will be able to better preemptively respond to the trajectory of this pandemic.

Data & Methods

Mobility and commute data

Mobility data are provided by Cuebiq, a location intelligence and measurement platform. Through its Data for Good program (`https://www.cuebiq.com/about/data-for-good/`), Cuebiq provides access to aggregated and privacy-enhanced mobility (see below) data for academic research and humanitarian initiatives. These first-party data are collected from anonymized users who have opted in to provide access to their GPS location data anonymously, through a GDPR-compliant framework. Additionally, Cuebiq provides an estimate of home and work census areas for each user. In order to preserve privacy, noise is added to these "personal areas", by upleveling these areas to the Census Block Group Level [21]. This allows for demographic analysis while obfuscating the true home location of anonymous users and prohibiting misuse of data.

Assembling a panel of Cuebiq users

In order to make a consistent analysis over time, we choose a subset of the users in the data for which we can carry our analysis through time. At the most basic level, we choose a panel of users who were active for more than 12 days in January 2020. This subset includes 17 million anonymous users nationally.

The method of data collection is dependent on the operating system of the device. In one case, the device reports location information at regular time intervals, while in another location information is only transmitted when a "geofence" is tripped by the movement of a user. Due to differences in how these devices report location information, users whose devices use geofencing can go without observations if they stop moving. This presents a challenge because it is impossible to know whether lack of observation is really due to reduced mobility, or if it could be due to the user changing their in app permissions, or changes at the platform level. In this report, we do not systematically distinguish Android and iOS users; however, we observe that the proportions of users of each operating system are relatively even, and this distribution is similar across cities. Additionally, most aggregate behavioral measures do not exhibit major discrepancies when limited to only iOS or only Android users.

Commute Data In this analysis we want to understand the impact of recommended mobility restrictions, specifically how "smart work" or "work from home" policies impact commute patterns [22]. For this purpose, we filter our users to only those who have at least two privacy-preserving "personal areas" as inferred by Cuebiq and define moving between these personal areas as a commuting event. The data are aggregated to the census tract level for major urban areas by day. From this data we construct a network with census tracts as nodes and weighted edges between tracts representing the number of people moving between the tracts in a given day.

Mobility Data Commute data can give us a general sense for reduction in daily mobility, but it leaves out important everyday mobility, such as trips to the grocery store or for recreation. In order to evaluate the impact of restrictions on this more general mobility, we analyze data at two different levels of granularity: personal and city-wide.

At the personal level, we quantify the typical distance that a user moves on a given day by computing their *radius of gyration* [20]. We first compute the center of mass of all the observed locations of that user on that day. The radius of gyration is the standard deviation of the set of all distances the user traveled on that day, as measured from the center of mass. We then analyze the distribution of radii of gyration for all users on a daily basis before and after mobility was restricted. On a city-wide level, we focus on Combined Statistical Areas (CSAs) and estimate the mobility patterns of users in our data set among different CSAs. With this, we can estimate, for example, the number of people coming in

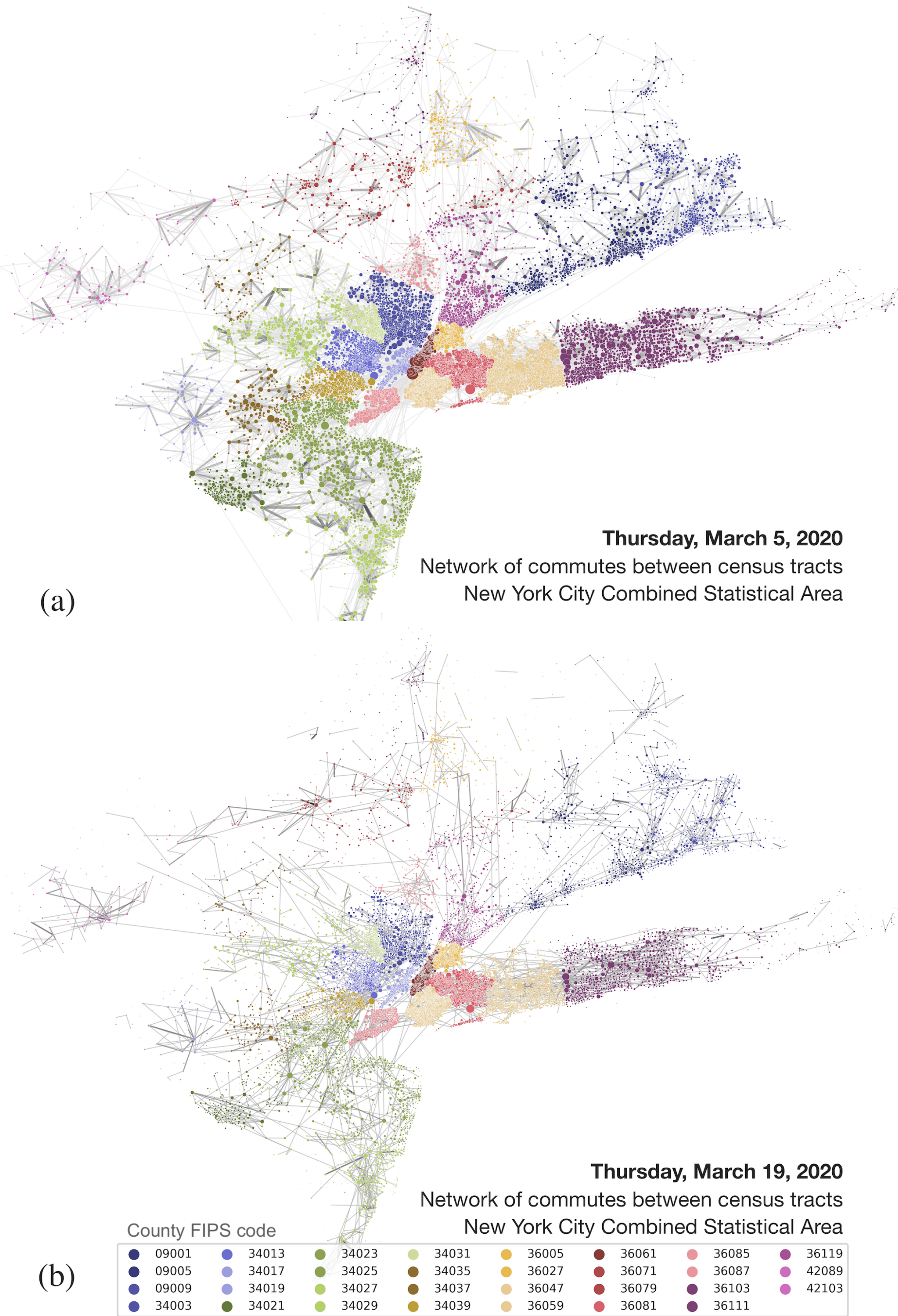

Figure 1: **Network of commuters between census tracts, New York City.** Each node corresponds to a census tract, and there exists a (weighted) edge connecting two census tracts if users commute to and from the privacy-preserving "personal areas" (see Methods) in each census tract. Nodes are colored by county FIPS code and are sized by *node strength* (sum of the weights on their edges, i.e., how many commutes flow through the node in a single day). **(a)** Thursday, March 5, 2020, before the large reduction in mobility. **(b)** Thursday, March 19, 2020, visually highlighting the large reduction in typical commuting patterns.

and out of each different CSA, and like before, we can compare these estimates before and after mobility restrictions. For this first report, we have included in our daily estimates only those users of mobile devices that were observed to be at exactly two different CSAs. In an updated version, we will include users that never leave a given CSA (so as to estimate intra-CSA mobility) as well as users that visit more than two CSAs in a day (e.g., layovers in a cross-country flight).

Results

The results in this report are organized into three scales of description of commuting and mobility changes during the COVID-19 pandemic in the United States. First, we quantify *mesoscopic* changes in mobility by calculating the commuting volume between census tracts within a number of cities as defined by U.S. Census Bureau Combined Statistical Areas (CSAs) [21]. An example of commuting patterns before and after the outbreak in New York City is shown in Figure 1. Next, we study *microscopic* changes in mobility, quantifying typical mobility patterns of users within a city by calculating their *radii of gyration* [20]. Lastly, we quantify *macroscopic* changes in mobility by calculating the volume of users who visit two CSAs within 24 hours (i.e. inter-city travel). Overall, we observe a similar onset and magnitude of reduction in mobility across all CSAs included in this analysis. This is somewhat surprising, as different cities have been experiencing outbreaks at different times, and we briefly discuss this in the following sections.

It is important to note that these three analyses are a small selection of the types of analyses that are possible using these data. We selected these as they are key benchmarks for the calibration of large-scale metapopulation models of disease transmission, such as the Global Epidemic and Mobility Model (GLEAM) [23, 24, 25, 26, 4].

Changes in commuting patterns (mesoscopic): In general, by Monday, March 23, 2020, each of the 16 CSAs included in these analyses had experienced a reduction of approximately 50% in total commutes (Figure 2 shows five representative CSAs), with the biggest differences seen by the end of the week. Figure 2 shows the scale of these reductions in commuting volume. Every point corresponds to the fraction of commutes observed that day divided by the average for the same day of the week in earlier weeks before any restrictions were put in place. For example, on federal holidays such as Martin Luther King Jr. Day (January 20, 2020), we see a typical drop in commutes corresponding to city wide closures of schools, businesses, and governments in cities where the holiday is officially recognized. Importantly, by March 20, 2020, the total number of daily commutes is less than Martin Luther King Jr. Day across all cities included in this analysis.

There are other similar heuristic benchmarks for reduced mobility. For example, by Monday, March 16, 2020, in Seattle, the total number of daily commutes resembles that of a severe weather day from January 14, 2020, suggesting that the size of the reduction in commutes resembles that of a typical public school closure day.

There are slight individual differences between the different CSAs, and more work can be done to better understand the timeline and the effect of each local government's orders for reducing mobility as well as local governments' compliance with federal guidelines. For

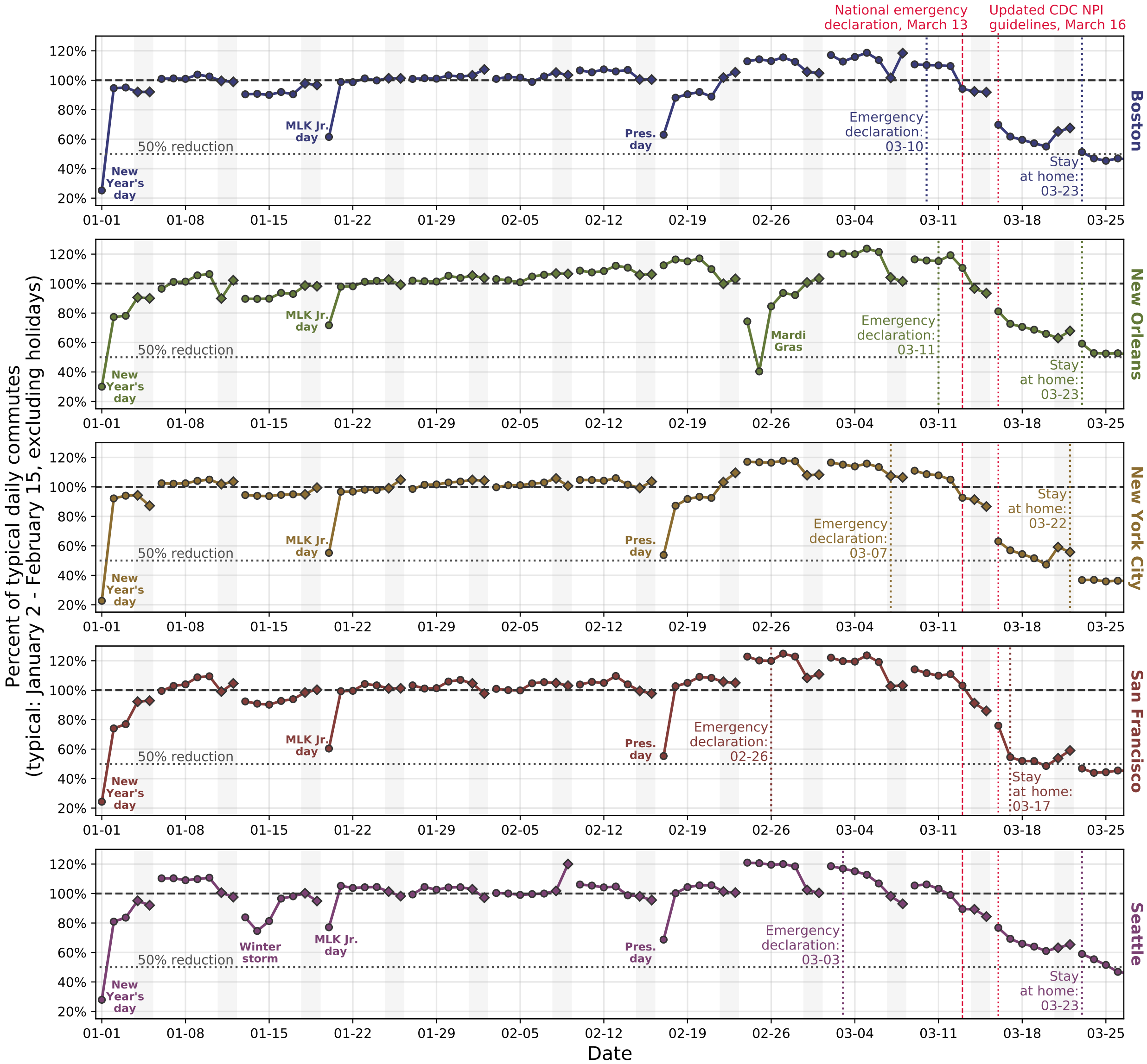

Figure 2: **Change in daily commutes within several CSAs.** Starting on Saturday, March 14, 2020, there is a reduction in the total number of daily commutes between census tracts across every CSA included in these analyses. Every point corresponds to the fraction of commutes observed that day divided by the average for the same day of the week in earlier weeks before any restrictions were put in place (i.e., the point for Friday, March 13 shows the fraction from the average number of commutes on all Fridays in January and February, excluding federal holidays). Shaded areas denote weekends.

example, one would expect to observe an earlier onset of the decline in commute volume in Seattle, which had an earlier onset of cases of COVID-19 than other cities [27] (by March 2, there were already several deaths), but we do not observe this in these data. Instead, Seattle's reduction in commuters more closely resembles that of Boston, with a gradual decline in commute volume starting around Friday, March 13, 2020. Regardless of their

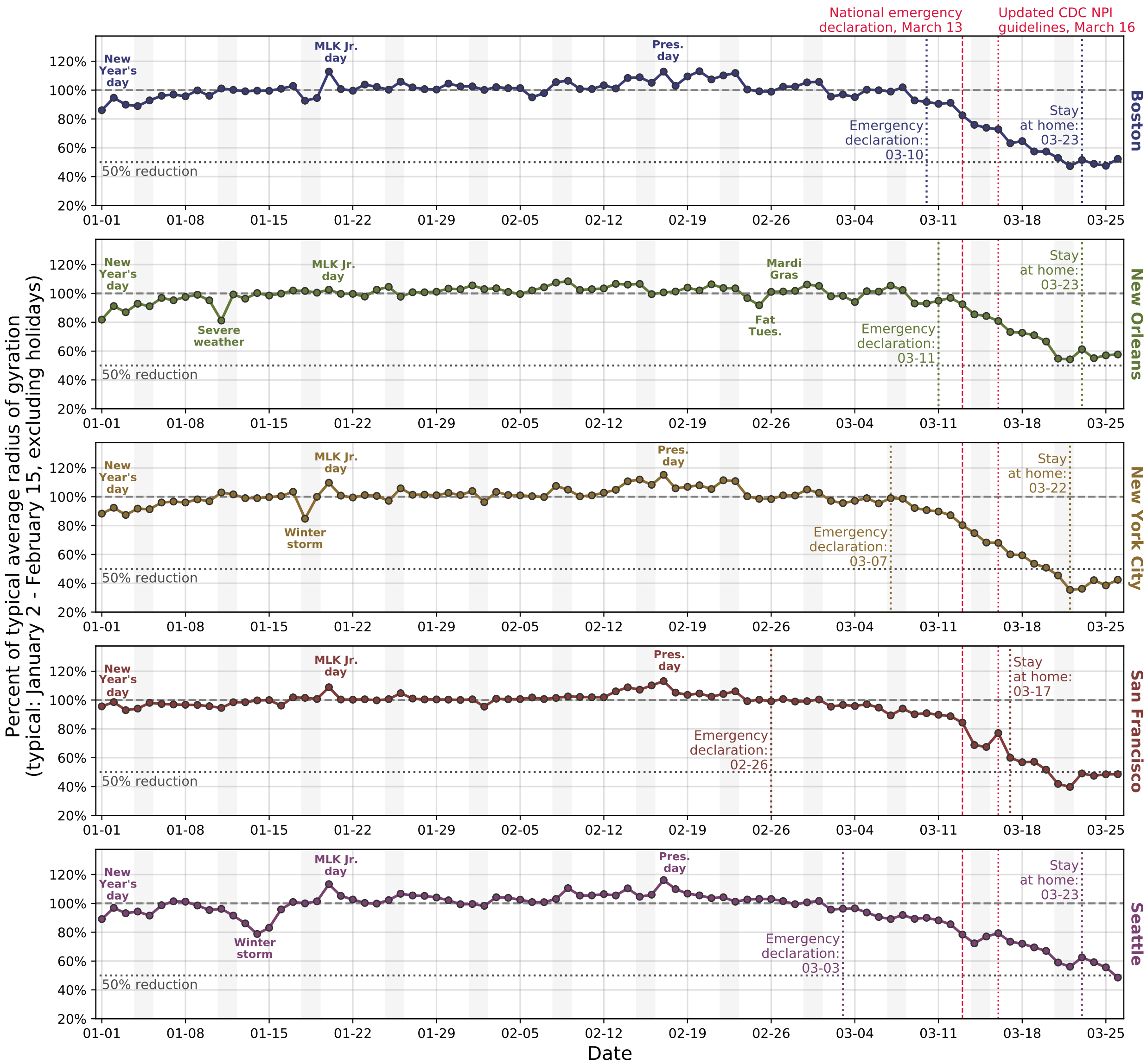

Figure 3: **Deviation from the mean daily radius of gyration.** While users in different cities likely have their own idiosyncratic, city-specific mobility patterns, we see a broadly similar pattern when we compare across cities: Typically, users have an average radius of gyration of between 1.85-2.17 miles (3000-3500 meters) on weekdays, with the average radius of gyration on the weekends increasing by approximately 30%. Of particular note, we observe a decreasing mean radius of gyration, starting between Friday, March 13, and Monday, March 16, among the CSAs included in these analyses.

specific dates of onset, however, we do observe a reduction in the number of commuters starting Monday, March 16, 2020.

Changes in anonymized individual mobility patterns (microscopic): Not only did we observe a reduced number of total commutes between census tracts in the cities we studied, we also observed a change in individual-user level behavior. On average, by March 24, 2020, the mean radius of gyration of users in our panel decreased between 40-60% relative to a typical weekday (Note: this was only calculated on user mobility within a single CSA, i.e., not with inter-CSA mobility). Similar results have been found by [28] for NYC. As defined in [20], the radius of gyration characterizes the size of a given user's trajectory in a single day, defined as:

$$r_g^a(t) = \sqrt{\frac{1}{n_a^c(t)} \sum_{i=1}^{n_c^a} (\vec{r}_i^a - \vec{r}_{cm}^a)^2} \tag{1}$$

where $\vec{r}_i^a$ is the vector of $i = 1, 2, ..., n_c^a(t)$ positions for user a, and $\vec{r}_{cm}^a$ is the center of mass of trajectory, $\vec{r}_i^a$. Note that this measure resembles a deviation from the center of mass of a given user, such that larger radii of gyration correspond to trajectories with positions that are far away from the trajectory's average position. In the current context, a smaller radius of gyration indicates that a typical user in our panel engages in shorter paths of motion throughout a city.

We observe that the radius of gyration typically increases on the weekends (i.e. users take longer trips during these days), but this trend is absent in the most recent weekend included in our data, therefore suggesting that individuals tend to stay home rather than taking trips.

Changes in inter-city mobility (macroscopic): In order to study the reduction in inter-city travel, we calculated the number of anonymous users who visited two separate CSAs in a single day (e.g. a user starts the day in San Francisco and ends the day in Denver), which offers a coarse notion of airline travel between major metropolitan areas. In every CSA included in these analyses, we observe a sharp decline in the number of users traveling between CSAs (Figure 4, left column), up to an 80% reduction of passengers traveling to or from San Francisco by Sunday, March 22, 2020. During the week of March 16, 2020, however most CSAs experienced up to a 60% reduction in inter-CSA mobility. These findings are encouraging for modeling and ultimately curtailing the spread of COVID-19, as they indicate a reduced likelihood of inter-city transmission of the virus.

Commuter network properties: In the Supplemental Information, we include a panel of results for each of the following cities: Atlanta, Boston, Chicago, Denver, Detroit, Los Angeles, Miami, New Orleans, New York, Orlando, Phoenix, Portland (Maine), San Francisco, Seattle, St. Louis, and Washington, DC. There, we also study statistical properties of a typical weekday/weekend commute network in each city, and compare them to commute networks from March 16 to March 20, 2020. We compare two key distributions of these commute networks: the edge weight distribution (i.e. the distribution of number of commuters between pairs of census tracts, including self-loops within a single census tract) and the node strength distribution (i.e. the distribution of the total number of commuters flowing through each census tract, or the sum of the edge weights of each node).

In general, we find that there are hubs in the commuter network: a few census tracts account for most of the commutes (i.e. commuting to downtown), while many census tracts have only a small number commuters (i.e. commuting to a small suburb). By March 20, for every CSA included in these analyses, two things happened to these distributions. First,

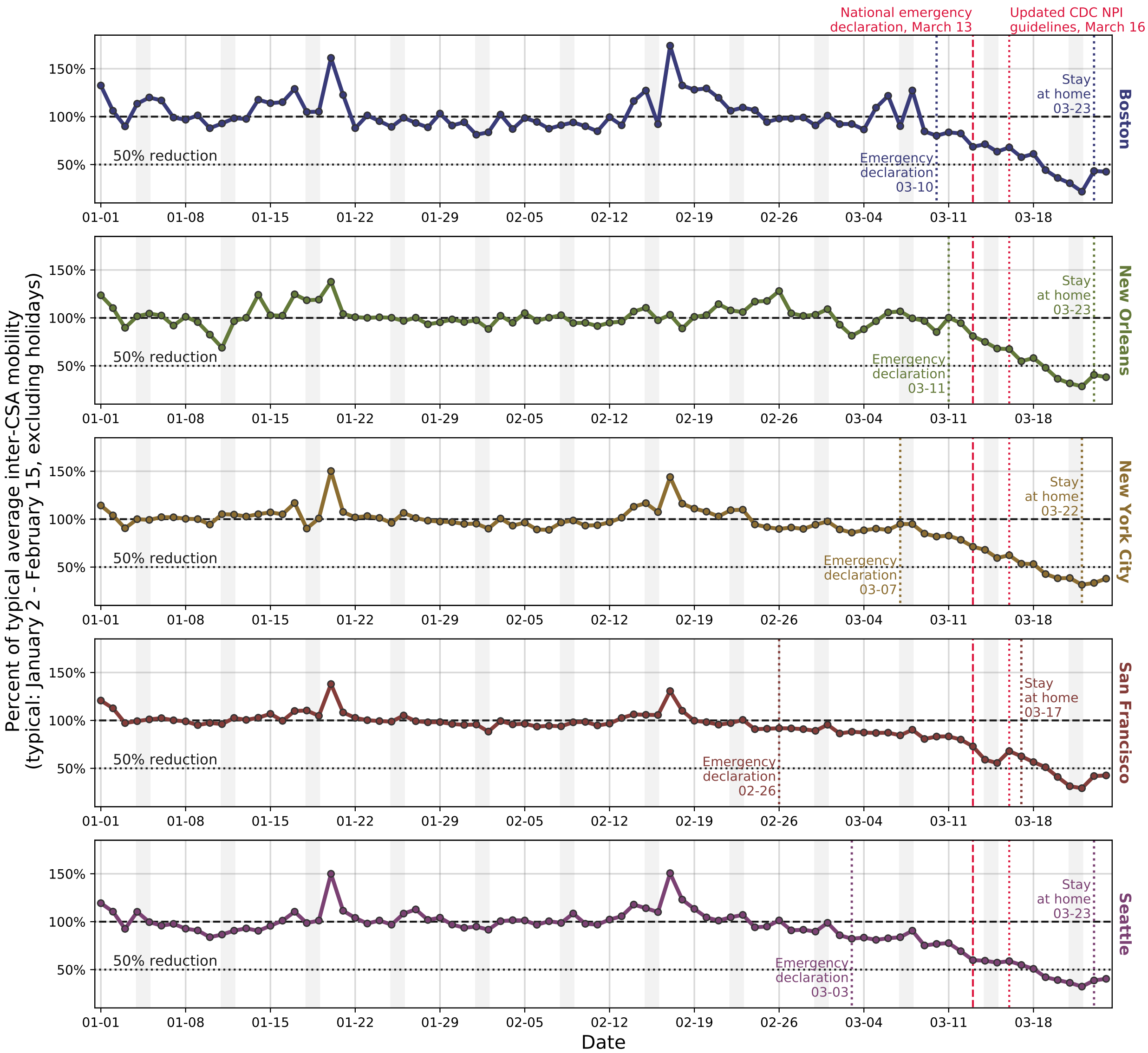

Figure 4: **Inter-CSA mobility over time.** Across all cities included in this report, we observe typical weekday/weekend patterns of mobility between other CSAs, showing more inter-CSA mobility on Fridays, Saturdays, and Sundays. In this plot, we show the change in inter-CSA mobility over time, normalized by each CSA's average inter-CSA mobility, per day of the week (i.e. Mondays are compared to other Mondays, etc.). Steep declines in inter-CSA mobility occur, starting in early March, with the most drastic declines starting the week of March 16, 2020. Individual CSAs show slight differences in terms of the onset or magnitude of the reduction, and further research will seek to associate these differences with guidelines and orders put in place by local officials in the CSA.

the tails of edge weight and node strength distributions both decreased, which indicates that fewer people are commuting to the high-commute-volume census tracts. Second, the fraction of census tracts with low commuter volume increases, which indicates that across a given CSA, most census tracts encounter even fewer commuters than they typically do. As a first step, both of these findings are positive (from the perspective of modeling and fighting the COVID-19 pandemic) in that they show city-wide reductions in mobility, which can be viewed as a proxy for the expected number of contacts that an individual has in a day that could result in transmission of the disease.

Conclusions

It is vital to quantify the effect of any major policy intervention. In order to accurately calibrate epidemic models of the COVID-19 pandemic, we must understand large-scale, population-wide changes in mobility that have occurred in many countries in early and mid-March 2020. In this report, we have taken a first step towards using high temporal resolution, anonymized location data from millions of devices to build a preliminary understanding of the effect of work from home policies, mobility restrictions, job loss, and shelter-in-place orders on urban and inter-urban mobility.

References

[1] The White House, Coronavirus Guidelines for America, `https://www.whitehouse.gov/briefings-statements/coronavirus-guidelines-america/` (2020). [Online; accessed 28-March-2020].

[2] Associated Press, UN health agency: Virus infections, deaths rising "considerably;" 85% of new cases are from Europe and US, `https://apnews.com/2476fecbeae06aa4a1183217722cd148` (2020).

[3] S. Lai, *et al.*, *medRxiv* (2020).

[4] M. Chinazzi, *et al.*, *Science* (2020).

[5] M. U. G. Kraemer, *et al.*, *Science* (2020).

[6] D. Martín-Corral, A. Aleta, A. Pentland, Y. Moreno, E. Moro, Effectiveness of social distancing strategies for protecting a community from a pandemic with a data- driven contact network based on census and real-world mobility data, *Tech. rep.*, COVID-19 Social Distancing Strategies (2020).

[7] H. Regan, Italy announces lockdown as global coronavirus cases surpass 105,000, `https://edition.cnn.com/2020/03/08/asia/coronavirus-covid-19-update-intl-hnk/index.html` (2020).

[8] J. Burn-Murdoch, C. Tilford, K. Fray, S. Bernard, Coronavirus tracked: The latest figures as the pandemic spreads, `https://www.ft.com/content/a26fbf7e-48f8-11ea-aeb3-955839e06441` (2020).

[9] E. Pepe, *et al.*, *medRxiv* (2020).

[10] C. D, *et al.*, The early phase of the covid-19 outbreak in lombardy, italy (2020).

[11] H. Tian, *et al.*, *medRxiv* (2020).

[12] World Health Organization, Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19), https://www.who.int/publications-detail/report-of-the-who-china-joint-mission-on-coronavirus-disease-2019-(covid-19) (2020). [Online; accessed 28-March-2020].

[13] M. Fisher, C. Sang-Hun, How south korea flattened the curve (2020).

[14] D. Normile, Coronavirus cases have dropped sharply in south korea. what's the secret to its success? (2020).

[15] European Commission, Coronavirus response: Transport measures, https://ec.europa.eu/transport/coronavirus-response_en (2020).

[16] G. St-Onge, V. Thibeault, A. Allard, L. J. Dubé, L. Hébert-Dufresne, *arXiv:2003.05924* (2020).

[17] U. B. of Labor Statistics, Workers who could work at home, did work at home, and were paid for work at home, by selected characteristics, averages for the period 2017-2018 (2019).

[18] C. Kang, D. Alba, A. Satariano, Surging traffic is slowing down our internet (2020).

[19] U. D. of Labor, March 26, 2020: Unemployment insurance weekly claims report (2020).

[20] M. C. González, C. A. Hidalgo, A.-L. Barabási, *Nature* **453**, 779 (2008).

[21] United States Census Department, Glossary, https://www.census.gov/programs-surveys/geography/about/glossary.html (2019).

[22] D. Thompson, The Coronavirus Is Creating a Huge, Stressful Experiment in Working From Home, https://www.theatlantic.com/ideas/archive/2020/03/coronavirus-creating-huge-stressful-experiment-working-home/607945/ (2020). Library Catalog: www.theatlantic.com.

[23] D. Balcan, *et al.*, *Proceedings of the National Academy of Sciences* **106**, 21484 (2009).

[24] D. Balcan, *et al.*, *Journal of computational science* **1**, 132 (2010).

[25] M. F. Gomes, *et al.*, *PLoS currents* **6** (2014).

[26] Q. Zhang, *et al.*, *Proceedings of the National Academy of Sciences* **114**, E4334 (2017).

[27] C. McNerthney, Coronavirus in washington state: A timeline of the outbreak (2020).

[28] M. Bakker, A. Berke, M. Groh, A. S. Pentland, E. Moro, Social distancing in new york city (2020).

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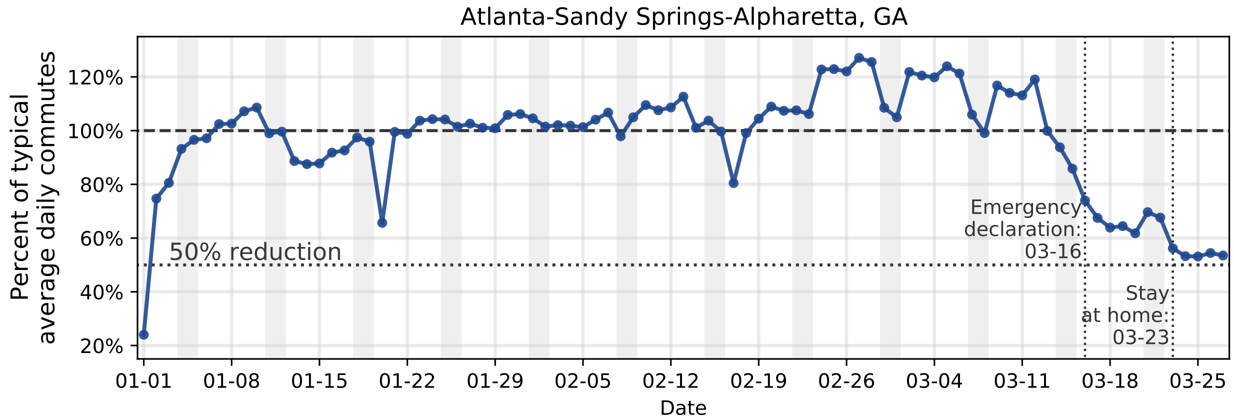
Supplemental Information

Individual city differences



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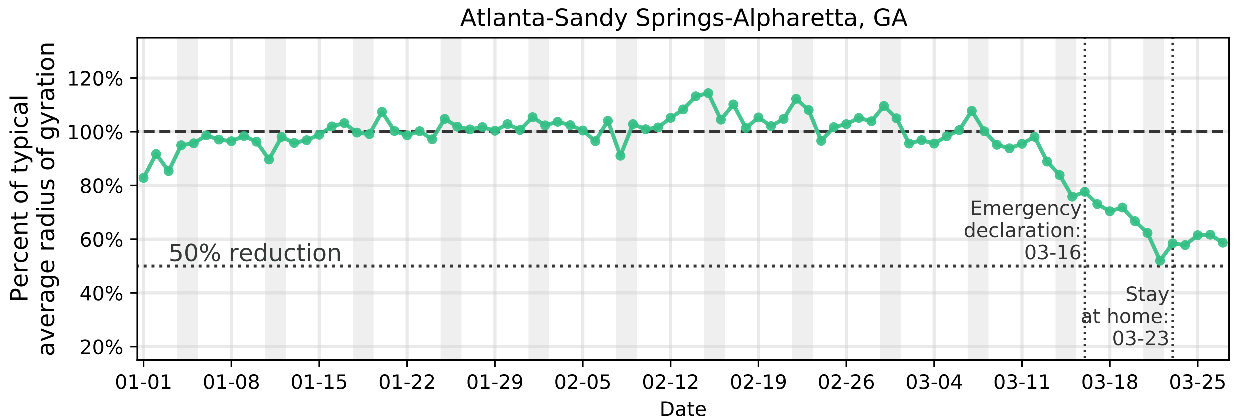

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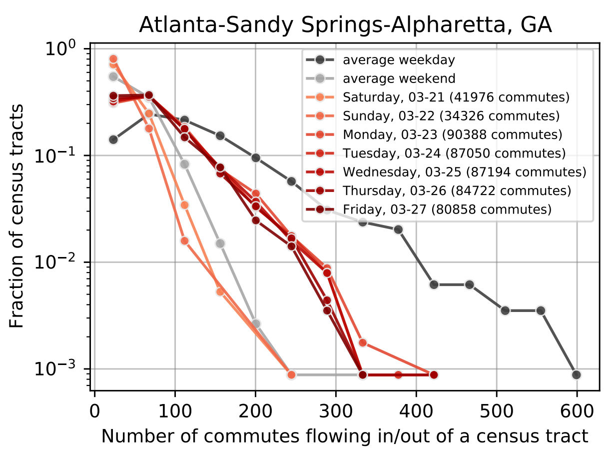

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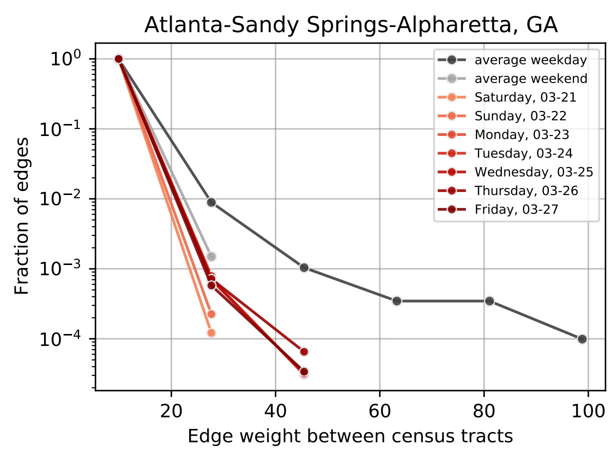

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Figure 5: **(a)** Total number of daily commutes in our sample over time in the Atlanta, Georgia Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.

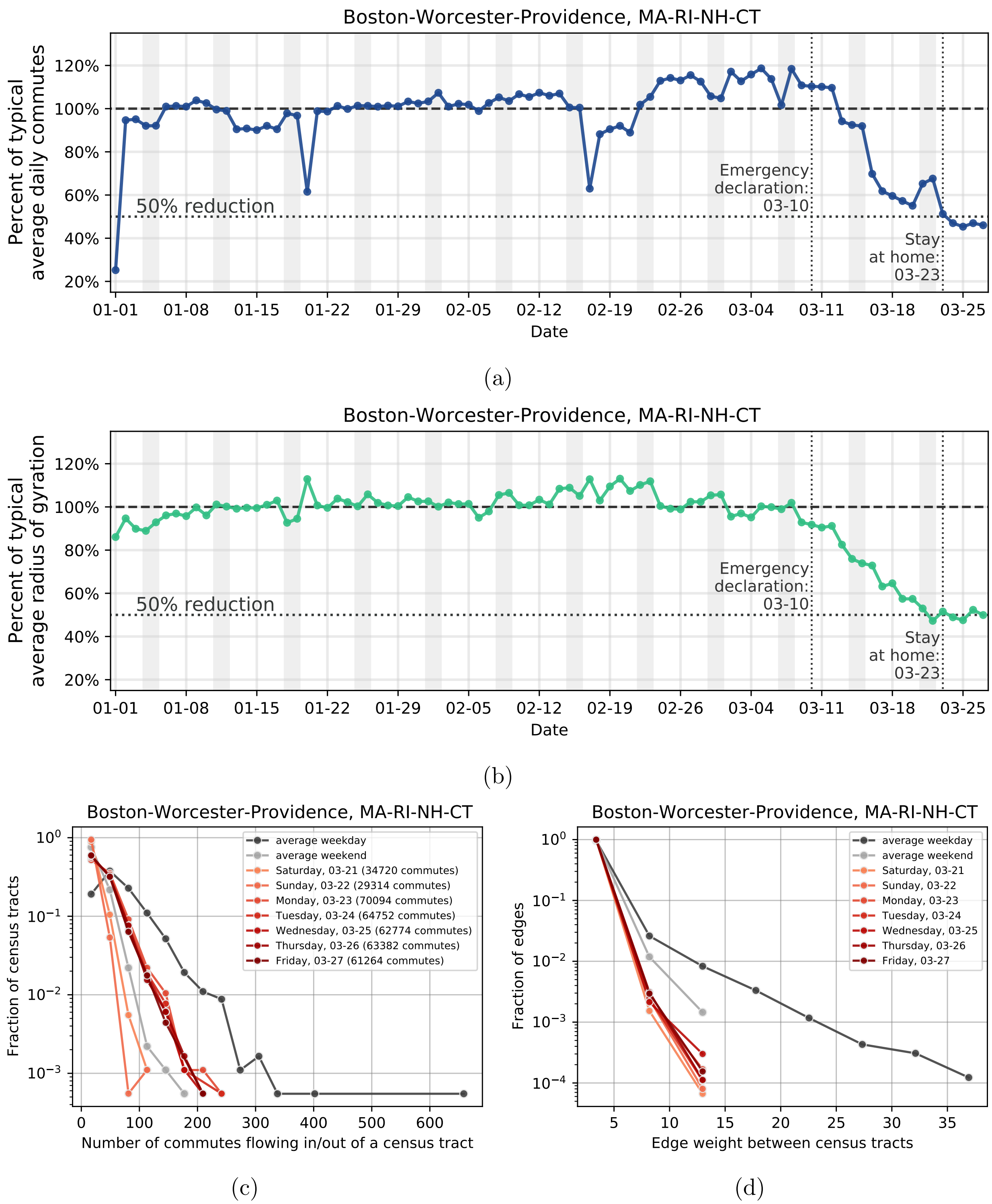
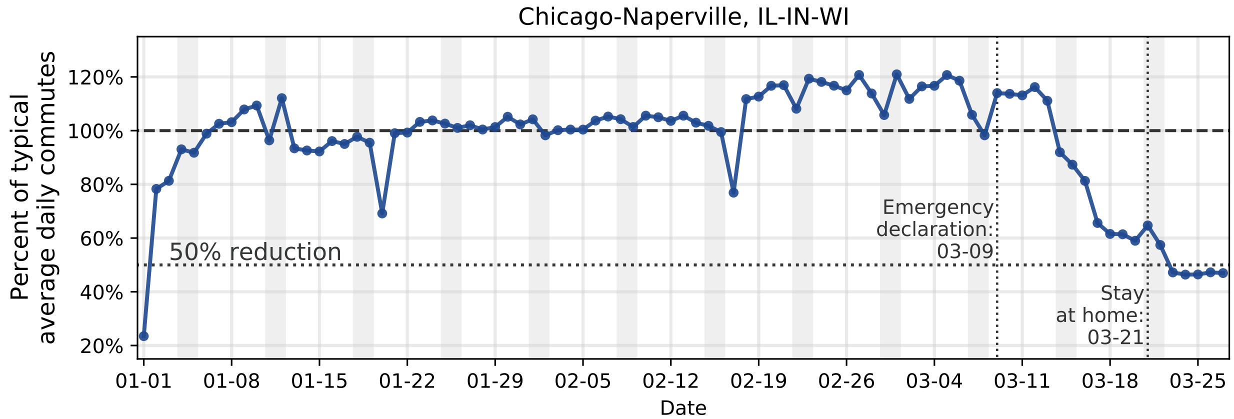


Figure 6: **(a)** Total number of daily commutes in our sample over time in the Boston, Massachusetts Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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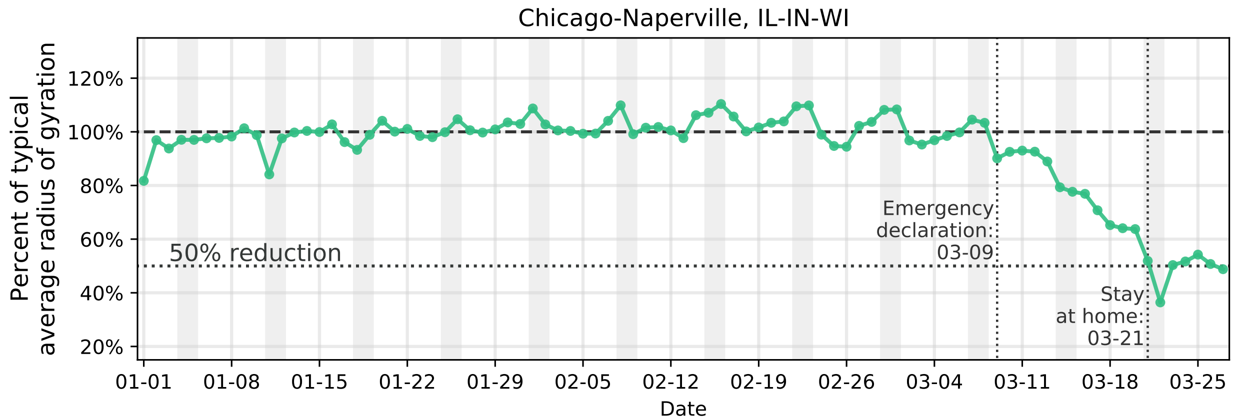

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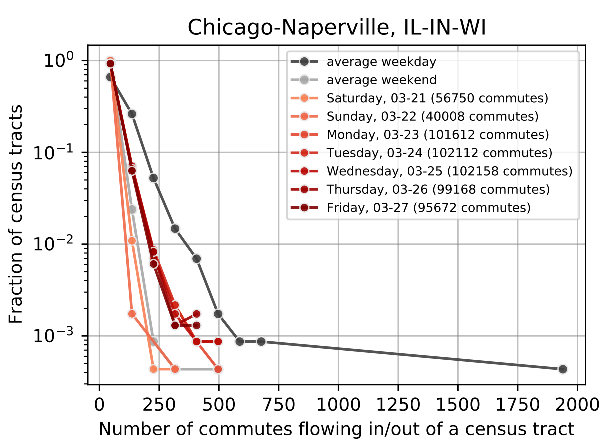

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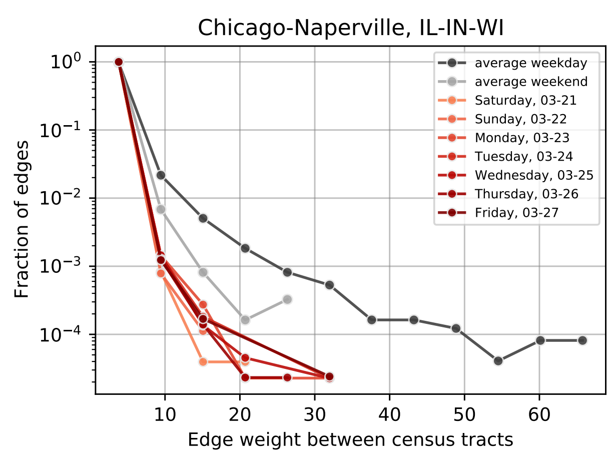

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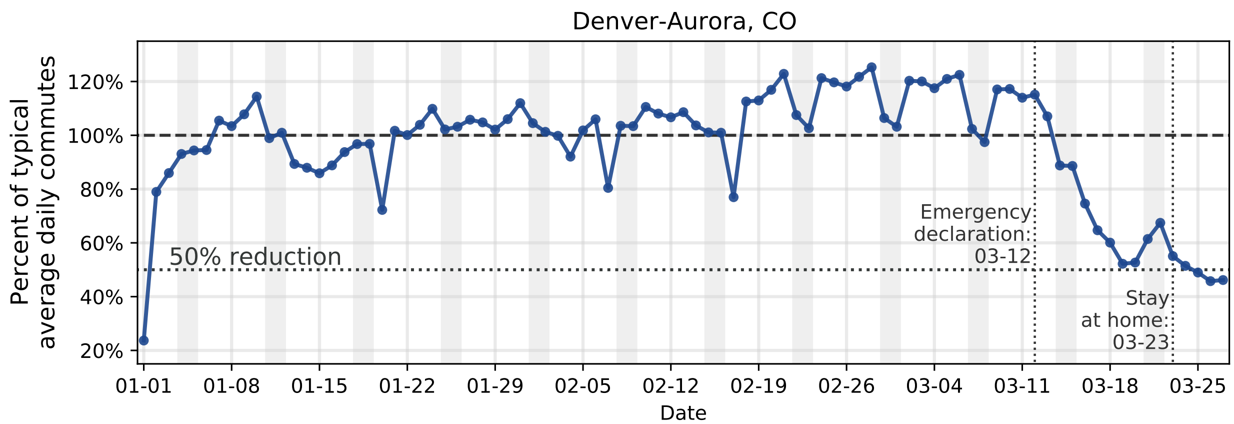
Figure 7: **(a)** Total number of daily commutes in our sample over time in the Chicago, Illinois Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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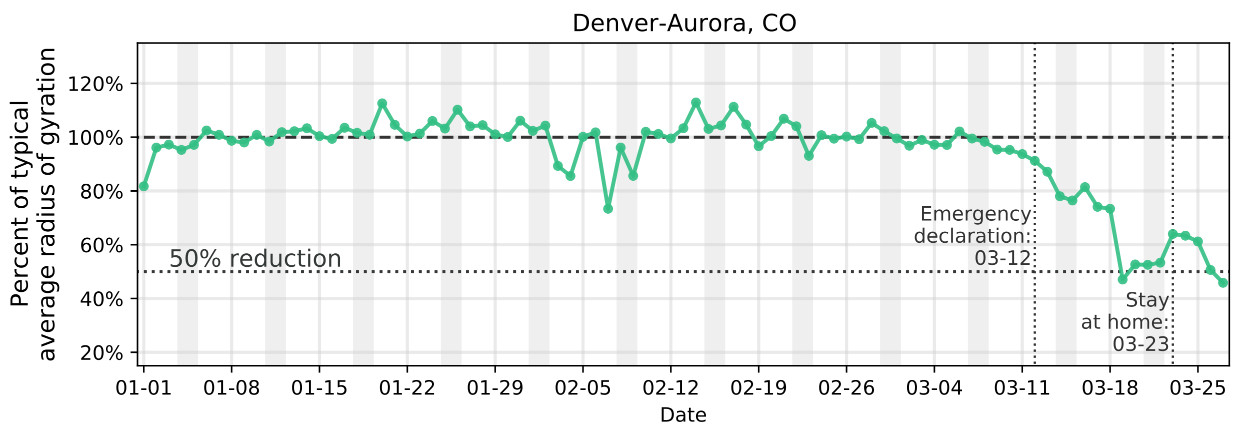

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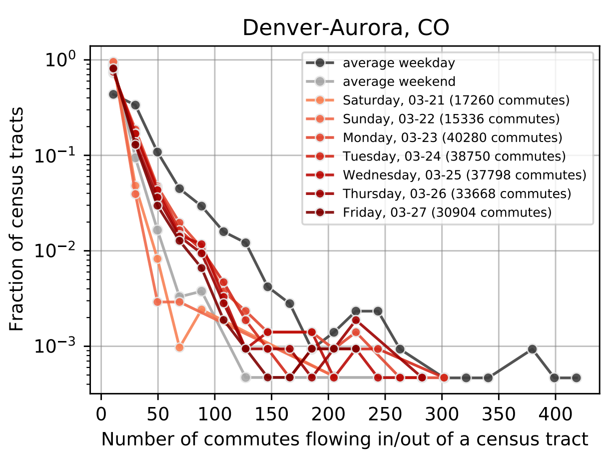

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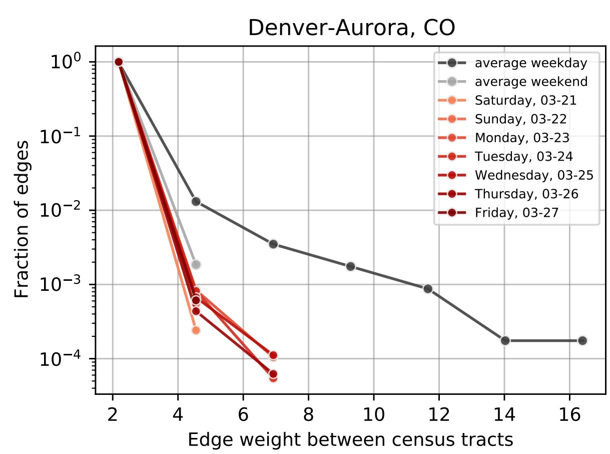

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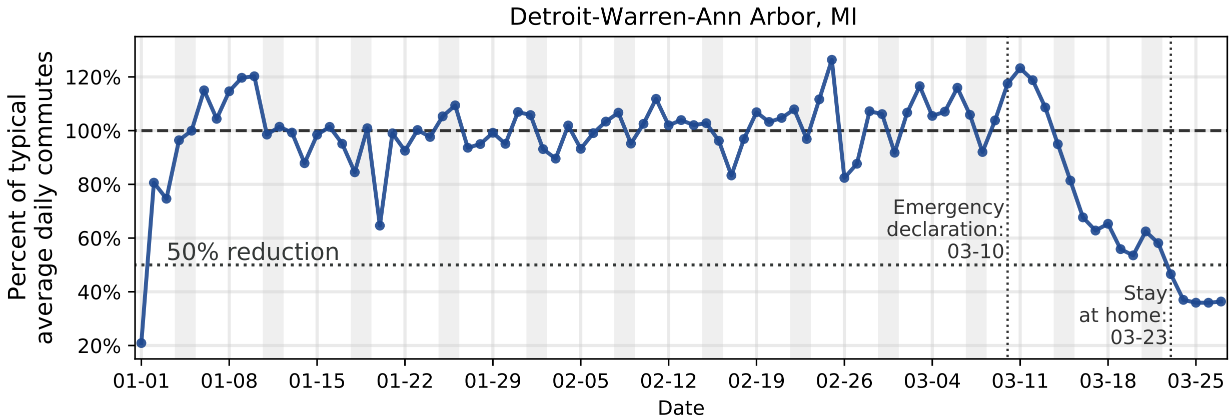
Figure 8: **(a)** Total number of daily commutes in our sample over time in the Denver, Colorado Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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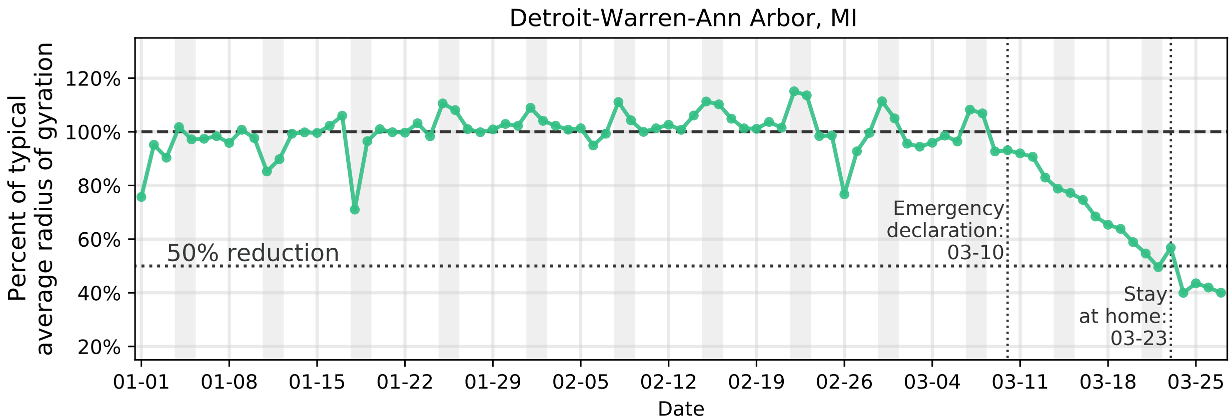

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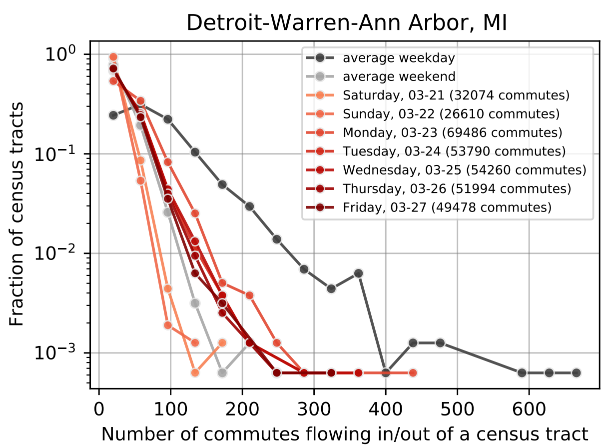

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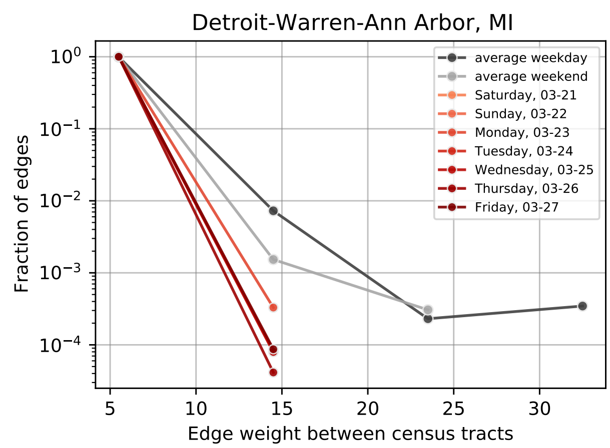
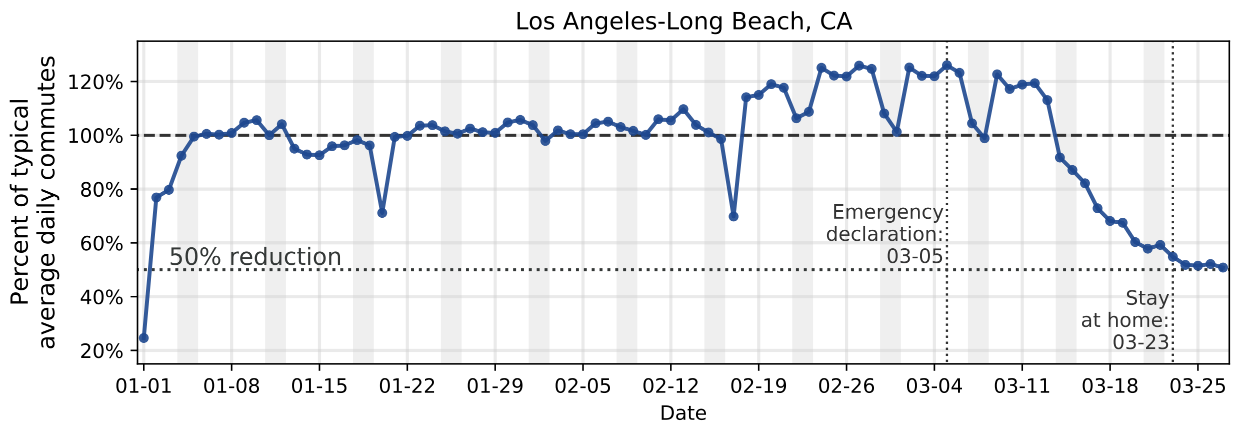


(d)

Figure 9: **(a)** Total number of daily commutes in our sample over time in the Detroit, Michigan Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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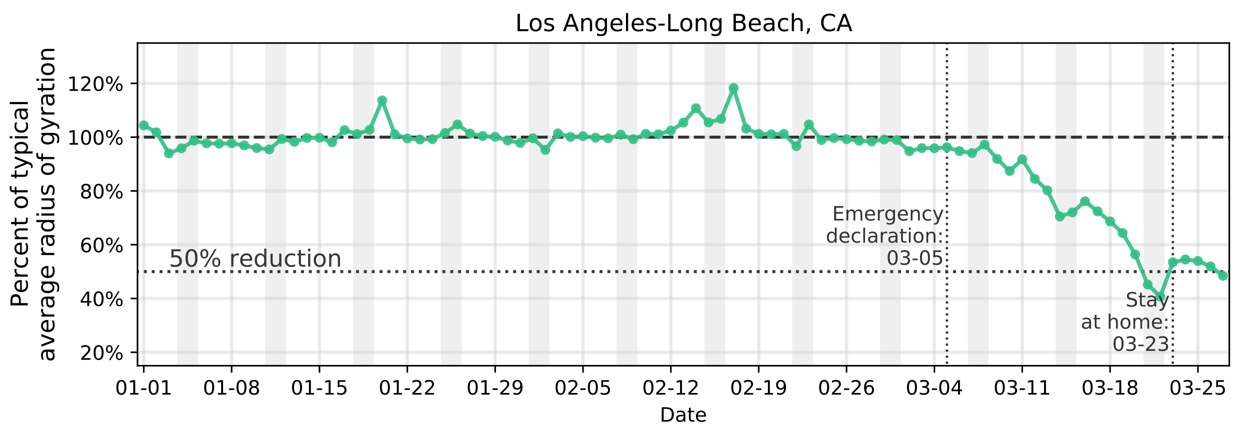

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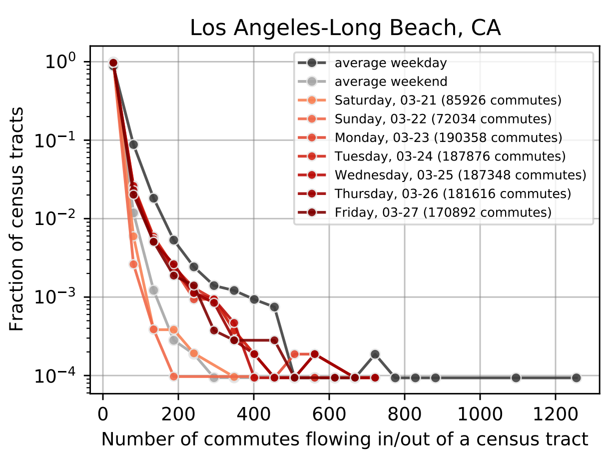

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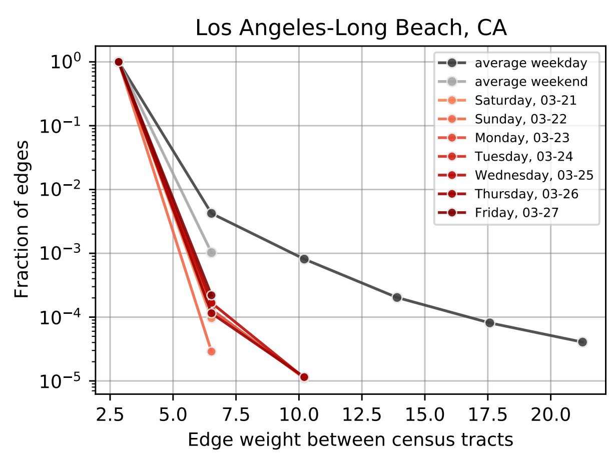
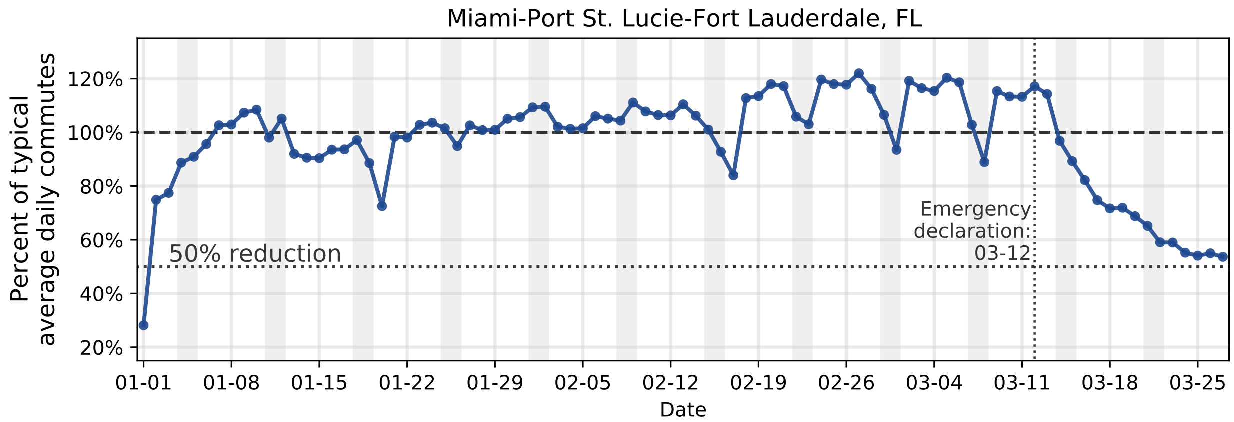


(d)

Figure 10: **(a)** Total number of daily commutes in our sample over time in the Los Angeles, California Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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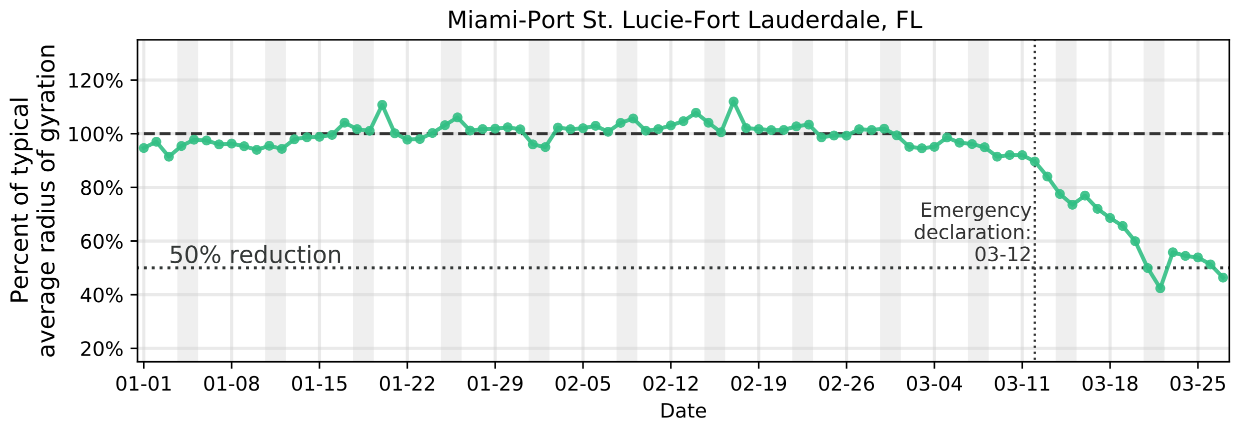

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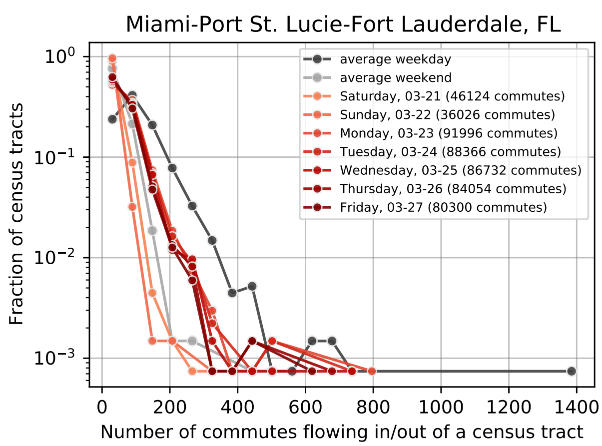

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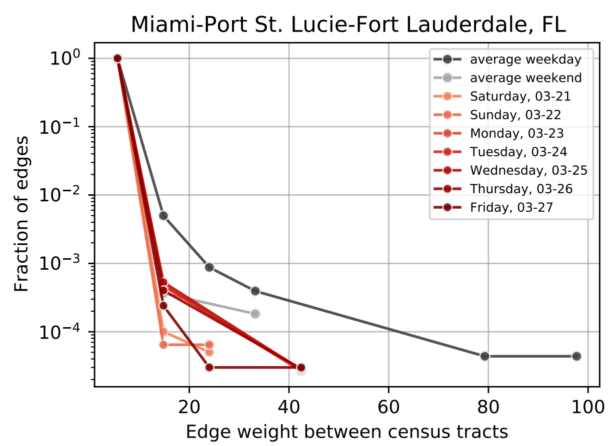
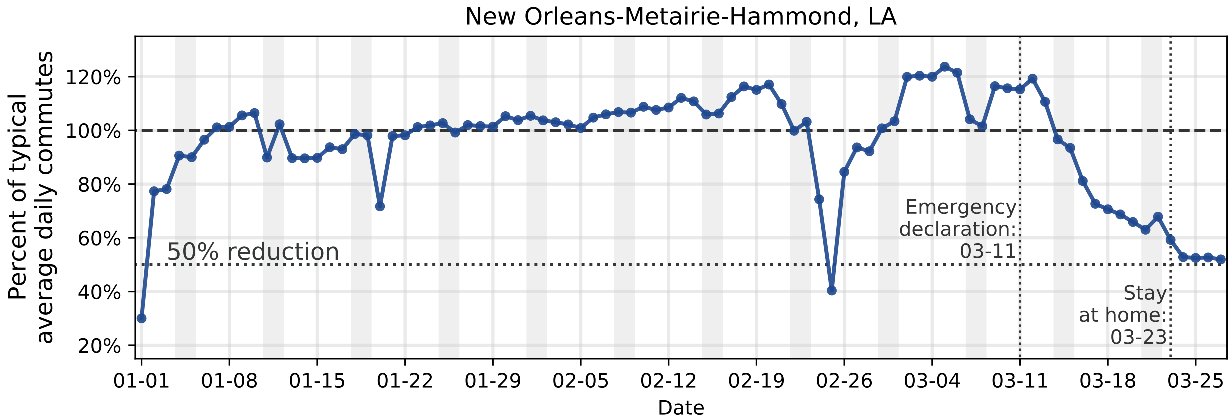


(d)

Figure 11: **(a)** Total number of daily commutes in our sample over time in the Miami, Florida Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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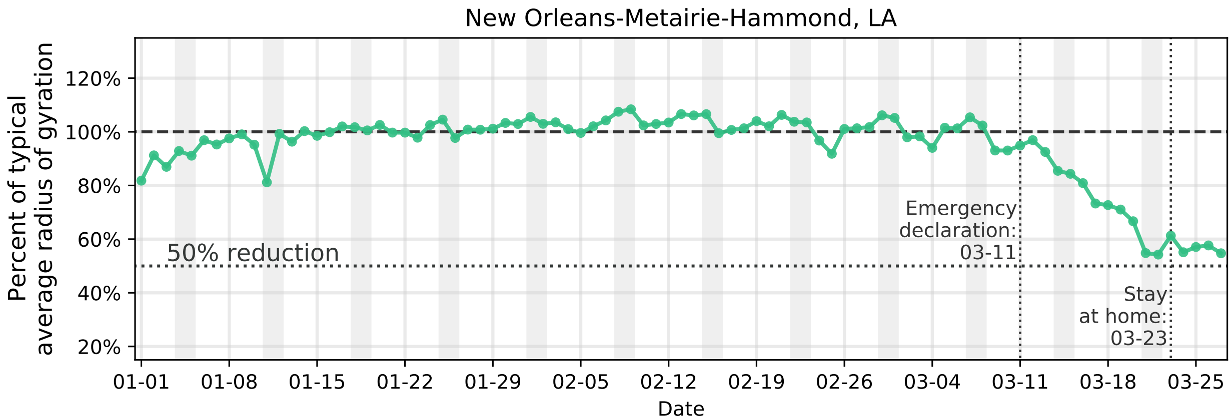

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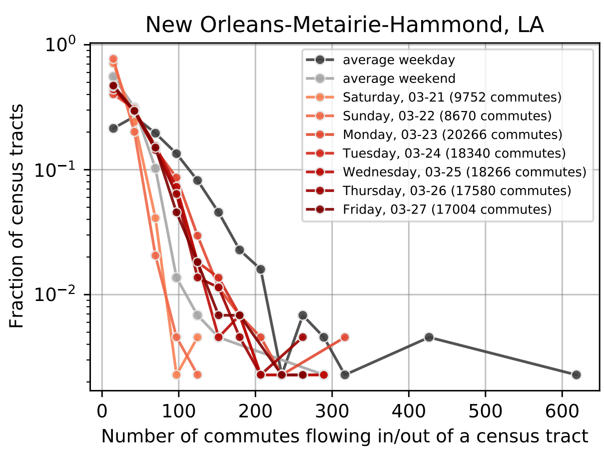

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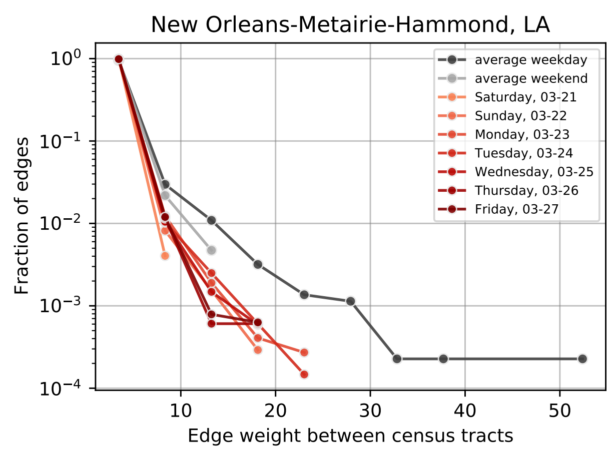
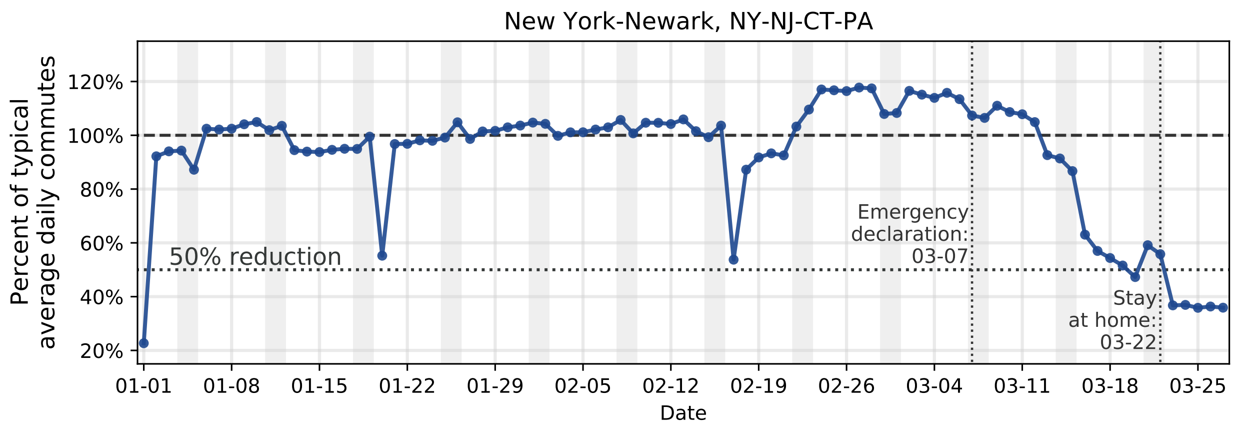


(d)

Figure 12: **(a)** Total number of daily commutes in our sample over time in the New Orleans, Louisiana Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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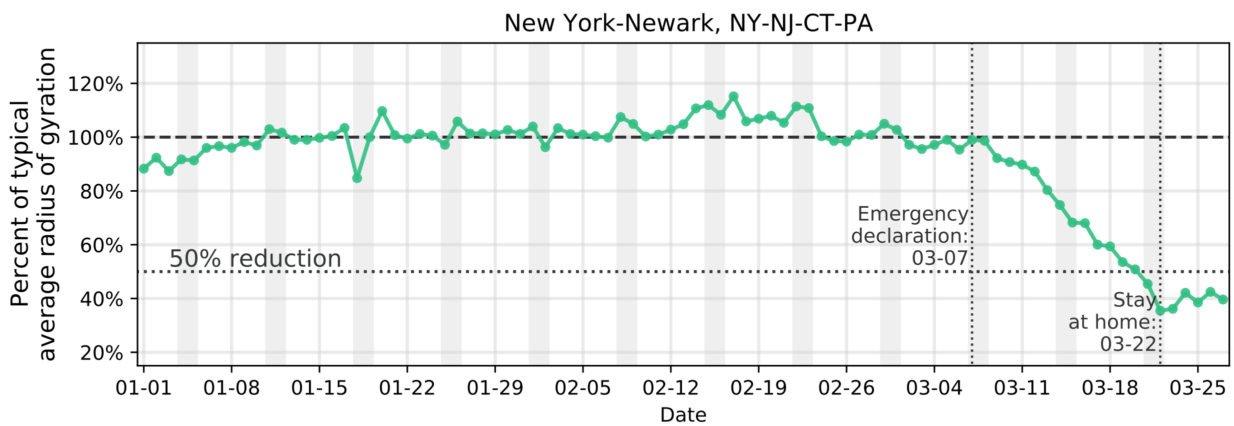

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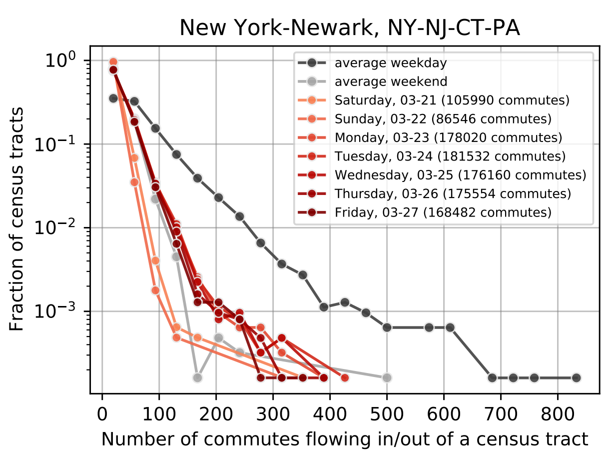

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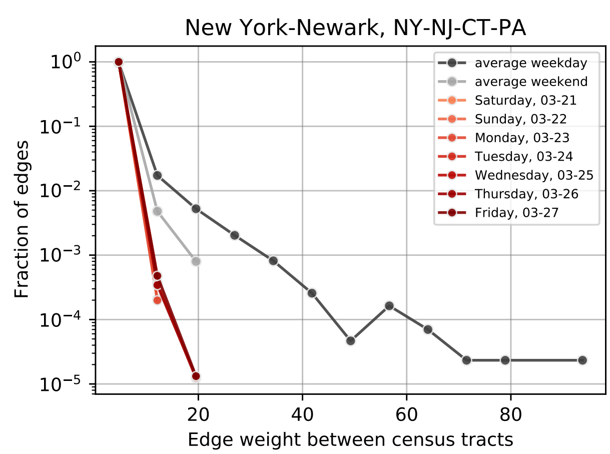
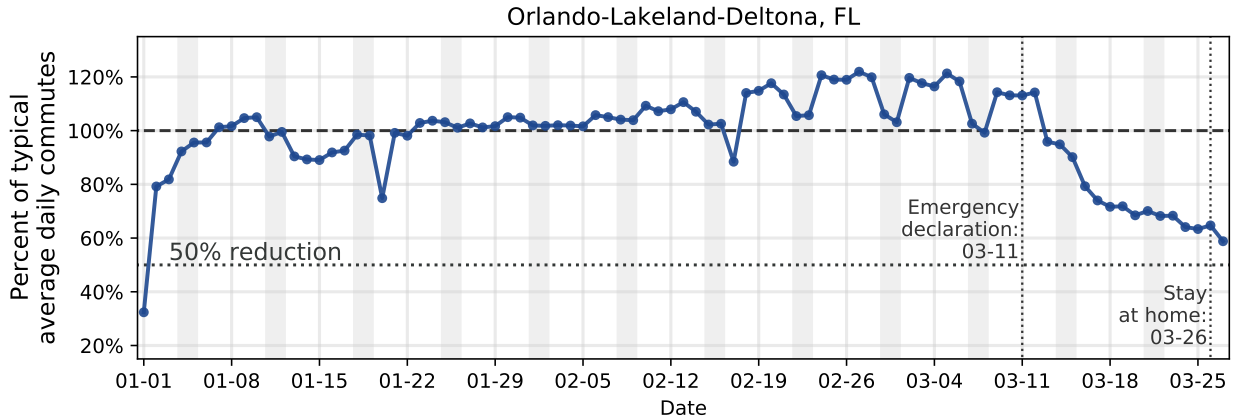


(d)

Figure 13: **(a)** Total number of daily commutes in our sample over time in the New York City, New York Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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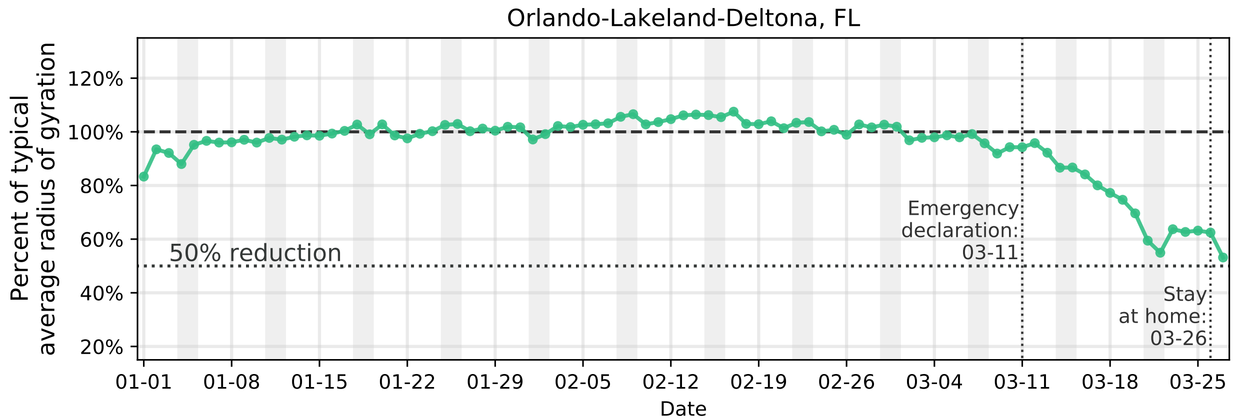

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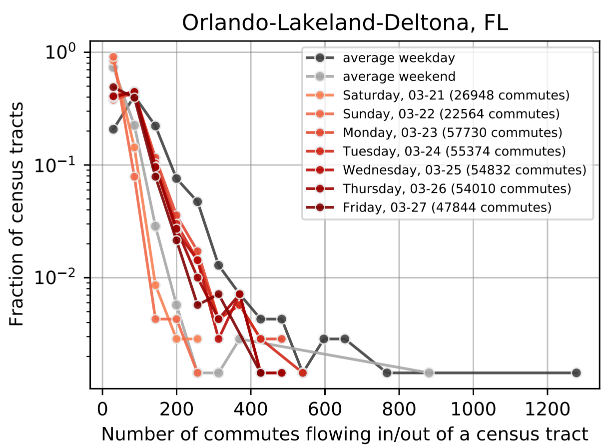

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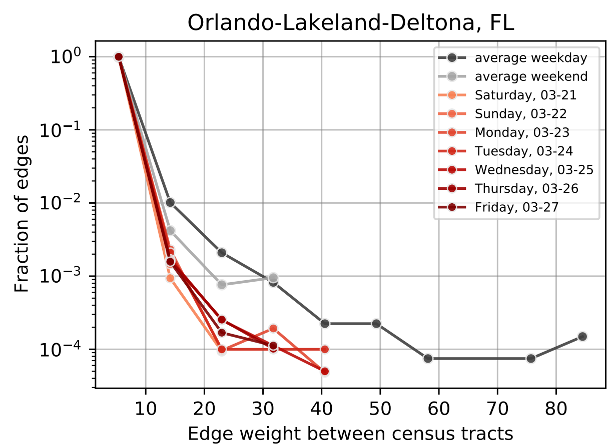
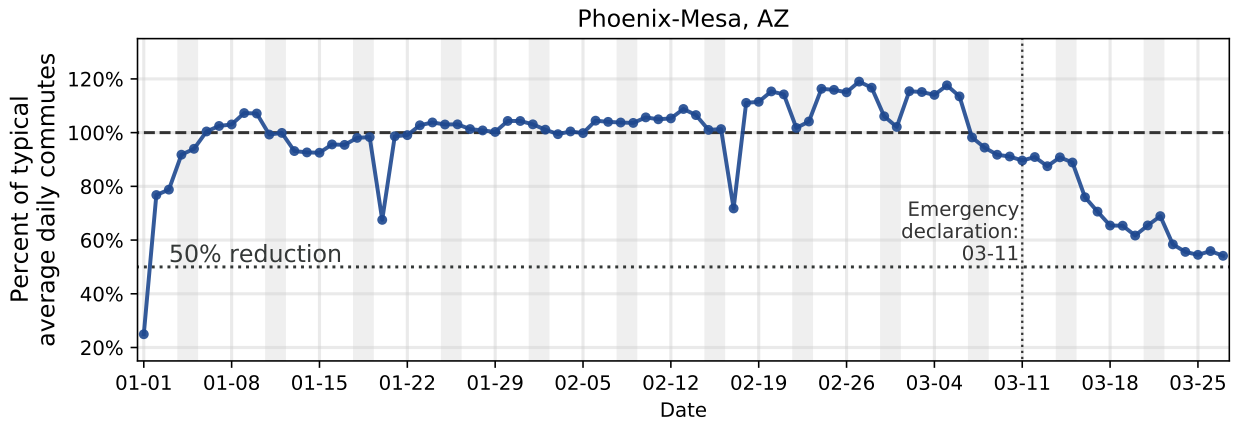


(d)

Figure 14: **(a)** Total number of daily commutes in our sample over time in the Orlando, Florida Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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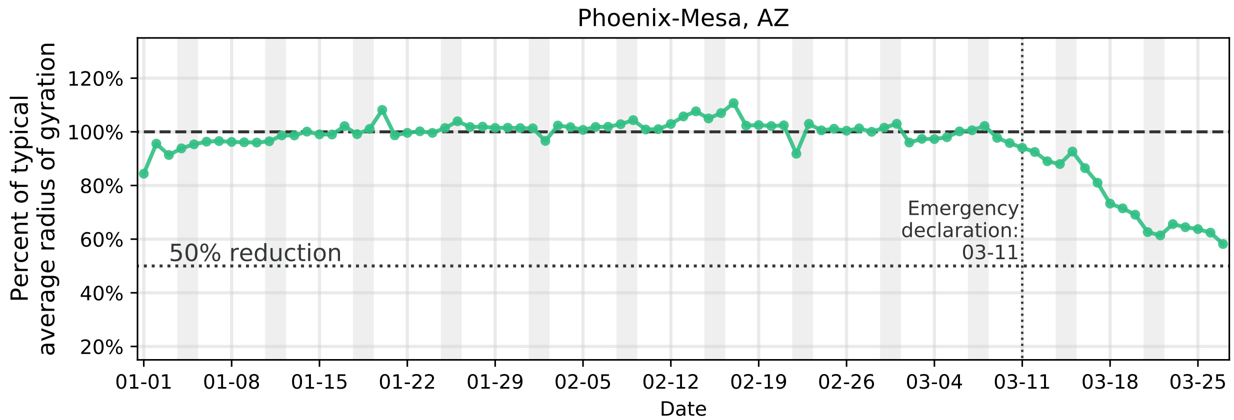

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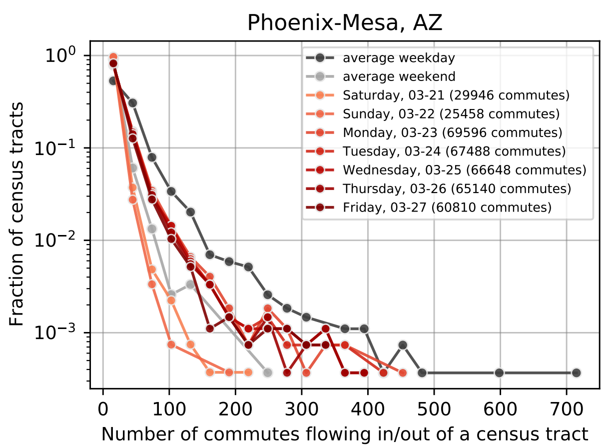

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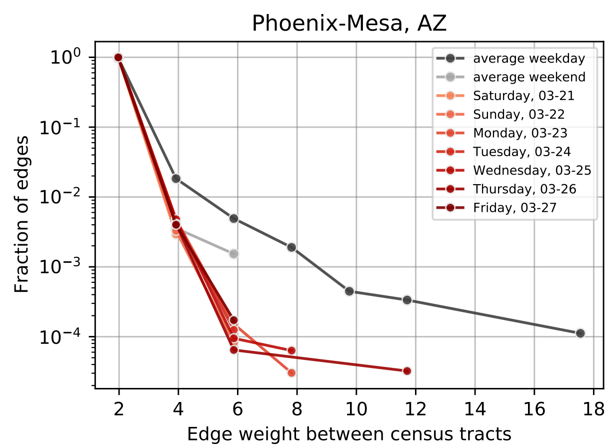
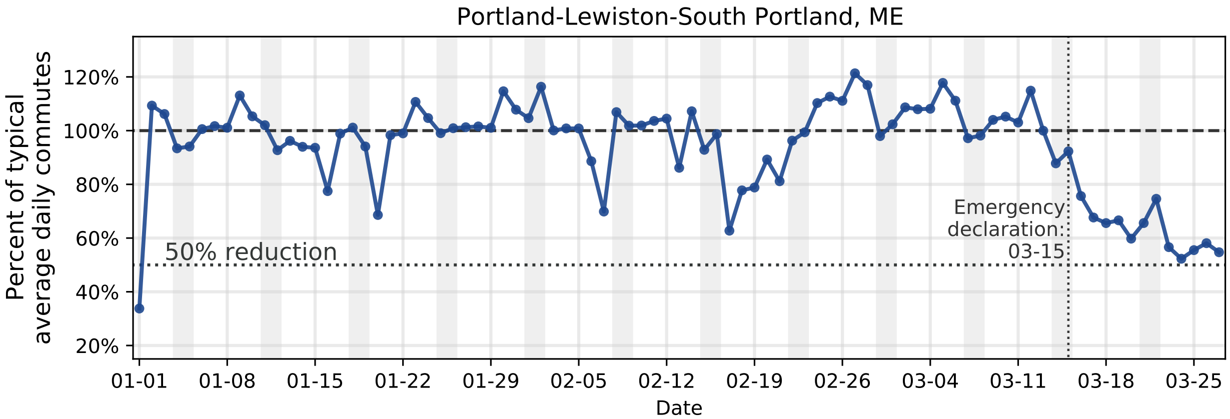


(d)

Figure 15: **(a)** Total number of daily commutes in our sample over time in the Phoenix, Arizona Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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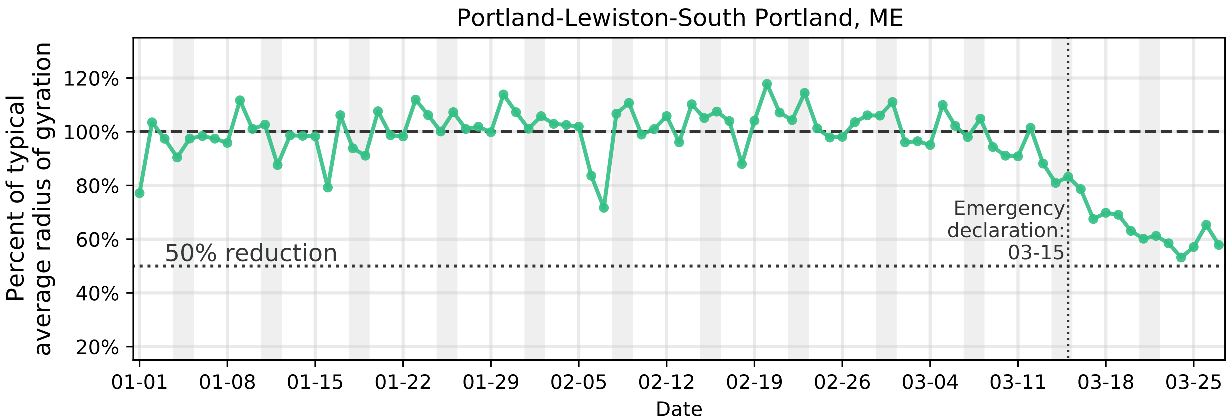

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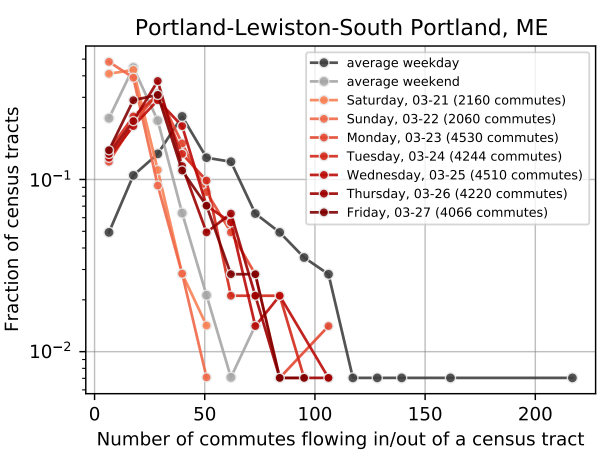

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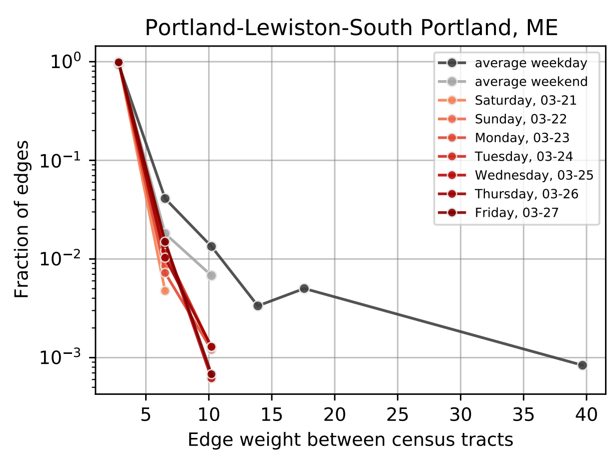


(d)

Figure 16: **(a)** Total number of daily commutes in our sample over time in the Portland, Maine Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.

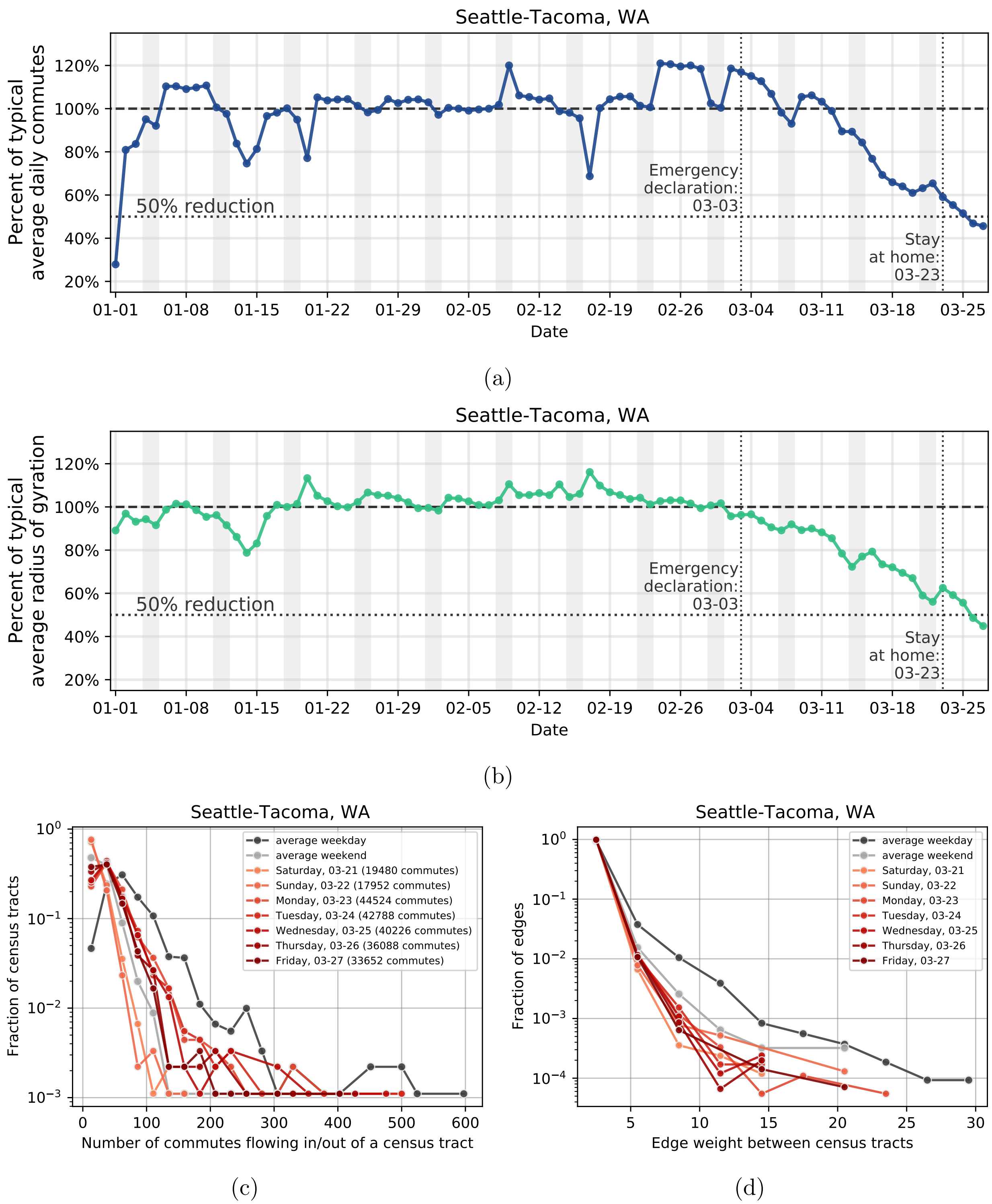
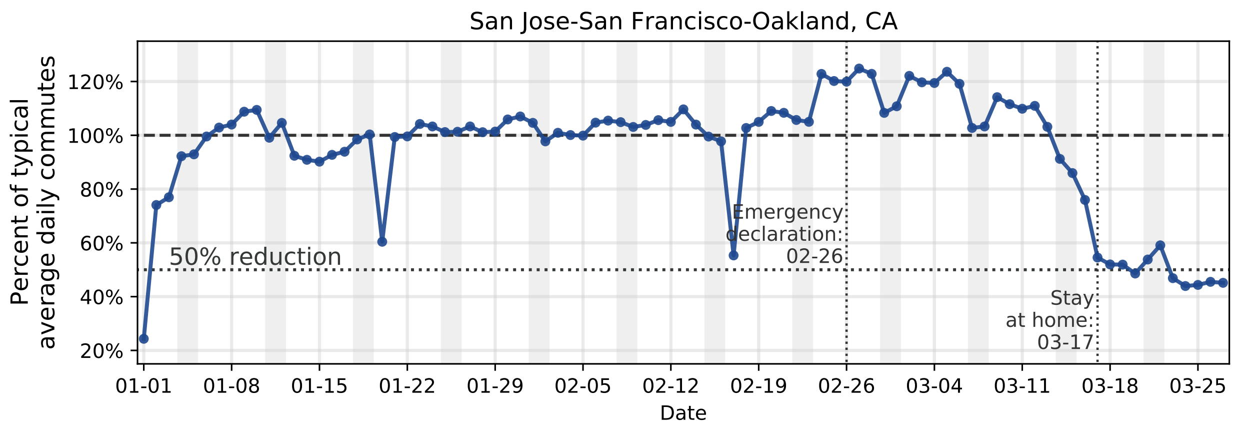


Figure 17: **(a)** Total number of daily commutes in our sample over time in the Seattle, Washington Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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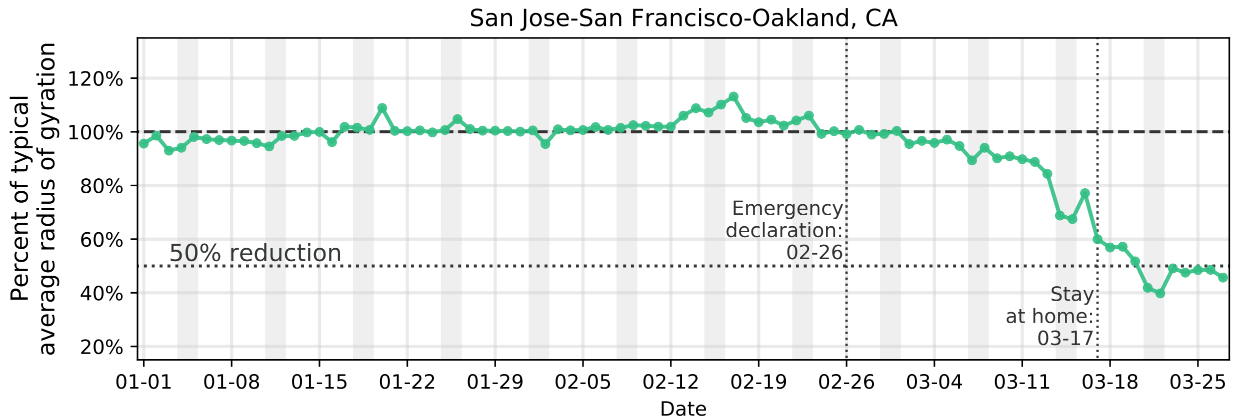

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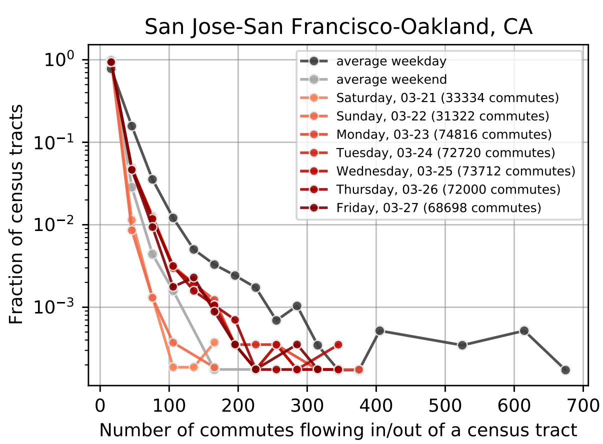

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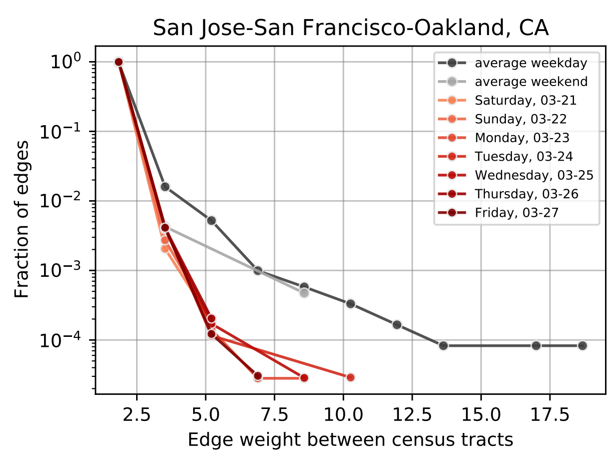
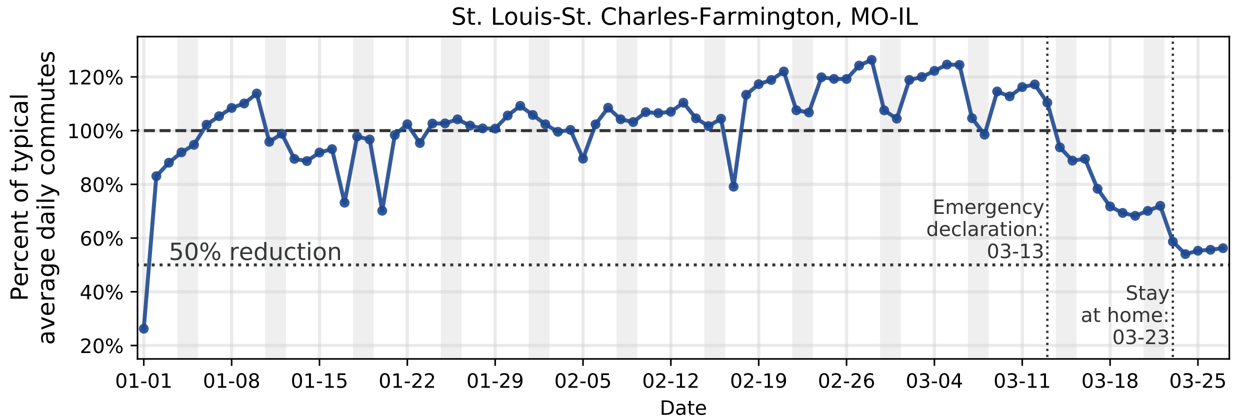


(d)

Figure 18: **(a)** Total number of daily commutes in our sample over time in the San Francisco, California Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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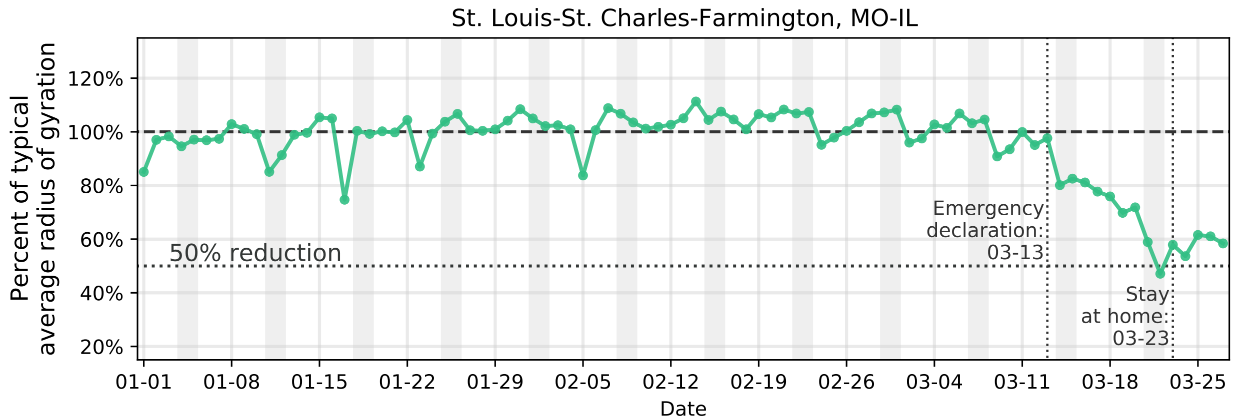

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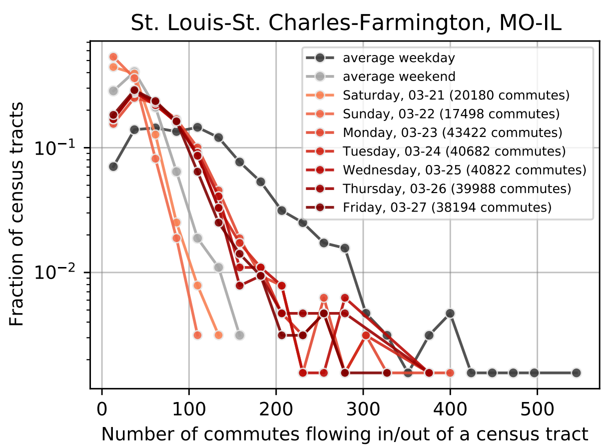

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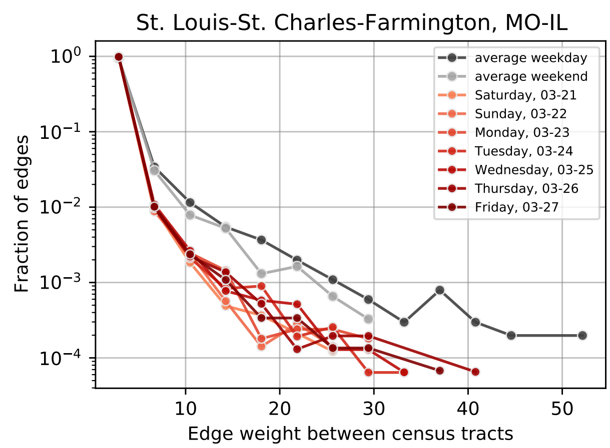
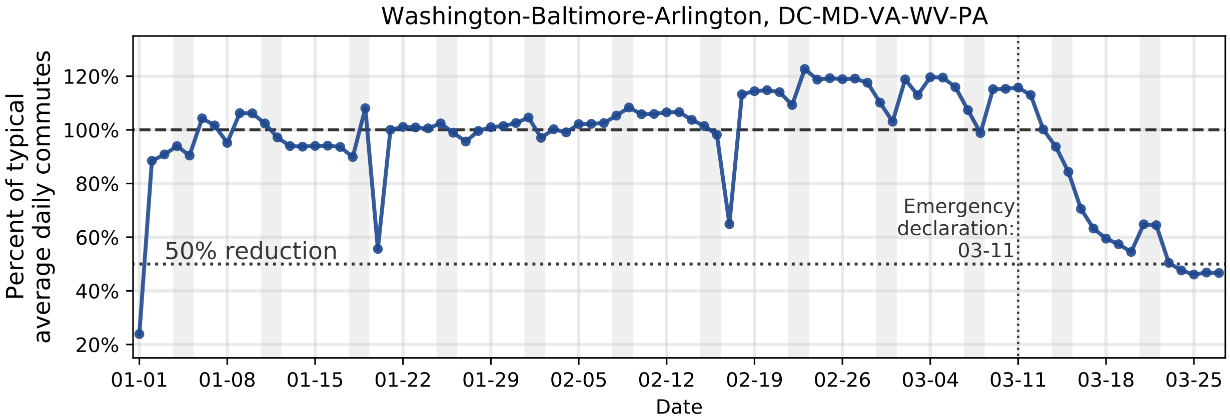


(d)

Figure 19: **(a)** Total number of daily commutes in our sample over time in the St. Louis, Missouri Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.



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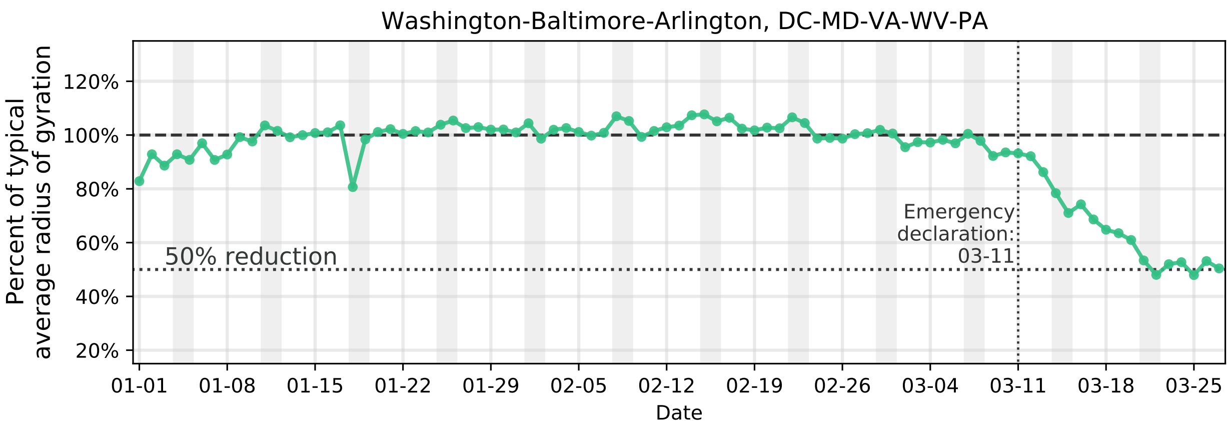

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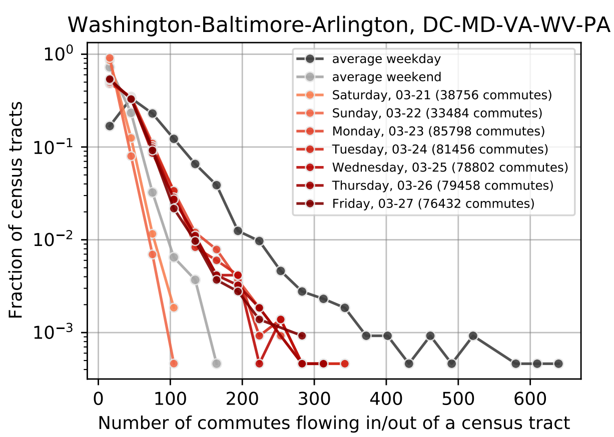

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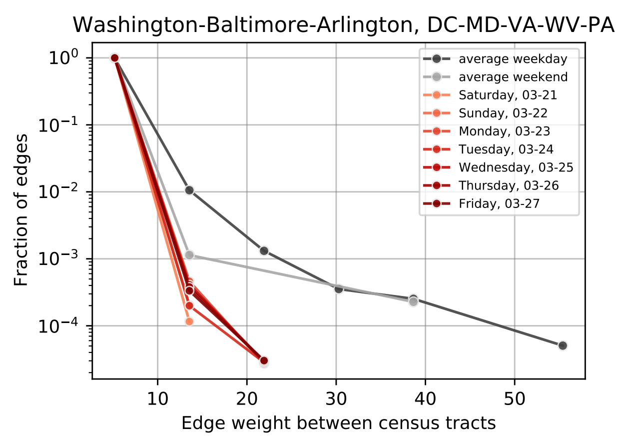

(d)

Figure 20: **(a)** Total number of daily commutes in our sample over time in the Washington D.C. Combined Statistical Area. **(b)** Radius of gyration for all users in CSA over time. **(c)** Distributions of node strength, measured as the sum of edges connected to a node (census tract), for average weekends and weekdays, as well as the week of March 16th. **(d)** Distributions of edge weight between census tracts over time.