Colorado Mobility Patterns During the COVID-19 Response

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Summary/Key Findings

- Coloradans have increased their time spent at home since the start of the epidemic. The reduction of time spent in public locations likely mitigated the spread of COVID-19, as shown in the Colorado epidemic model.
- Recent mobility patterns suggest concerning changes in behavior that may increase transmission of the SARS CoV-2 virus.
- Mobility patterns and response to policy are variable across the state.

Executive Summary

This report draws on a range of digital trace data to estimate the changes in mobility patterns exhibited by Coloradans in the wake of the COVID-19 pandemic. The report provides extensive details about the data used in these analyses, various strategies for summarizing the patterns in those data, ethical considerations for their use, and possibilities for incorporating such data into the modeling of COVID-19 projections for Colorado. This summary provides a brief overview of key findings in the report.

Overall, we note that Coloradans have increased their time spent at home since the start of the epidemic (see Figures 3 and 8, in particular). The reduced time spent in public locations likely mitigated the spread of COVID-19, as demonstrated in our team's corresponding Colorado epidemic model (see report, April 20). In part, these reductions followed from the statewide policy interventions implemented by Governor Polis– including both (1) the (mid-March) closure of ski resorts, bars, restaurants, and a select set of other businesses, which was largely coupled with the timing of school district closures across the state, and (2) the statewide "Stay-at-Home" order that was in effect from March 26 through April 26.

We note three exceptions to this general pattern. First, as seen across most of the figures in the report, many of these behavioral changes began before the respective orders took effect. That is, people appeared to voluntarily reduce their time spent in public locations *before* recommended or required to do so *and* appear to have begun relaxing those reductions before the expiration of the Stay-at-Home order. Second, the behavioral responsiveness to these orders varied substantially across locations in the state (see Figure 4, in particular). While the general pattern exhibited a precipitous drop, followed by gradual increases in time spent away from home, some counties demonstrated more extreme versions of this pattern than others. In contrast, others exhibited less dramatic responses (e.g., see Fort Collins in Figure 2). Third, the initial responsiveness to recommended reductions in time spent in public has begun to reverse.

Beyond these patterns illustrated in the report, we also highlight several other details briefly. First, mobility is one contributing factor among several that contribute to the risk of transmission of SARS-COV-2. These patterns must be read in conjunction with other concomitant changes–particularly the frequency of maintaining physical distance from others in public places and the use of face masks or other protective equipment. Second, these analyses require careful safeguards to maintain privacy protections for Colorado residents; we discuss these protections in some detail in the full report. And finally, while the description of these patterns is important to understand how people have responded to policy interventions, they also provide additional input for models of SARS-COV-2 transmission and COVID-19 outcomes for the population of Colorado.

Introduction

As the COVID-19 pandemic continues to evolve, a key dimension for both explaining what has already taken place and projecting future scenarios requires accounting for mobility patterns of the population (Buckee et al., 2020). Characterizing these patterns is essential in any attempt to model transmission dynamics and the effects of social distancing measures. Increasingly, scholars estimating these mobility effects are incorporating large-scale, near real-time data (Klein et al., 2020). To date, these assessments have largely focused on national patterns (Klein et al., 2020), or as after-the-fact explanations for patterns that drove transmission dynamics elsewhere (Panigutti et al., 2020; Queiroz et al., 2020; Ying et al., 2020). Such efforts necessitate coordination across teams, data harmonization across platforms, substantial protections to maintain appropriate privacy standards, and careful interpretation to accurately make use of this high volume data (Queiroz et al., 2020).

The objective of this report is to provide an overview of how we use mobility data to estimate how mobility data reveal observed behavioral patterns shaping the transmission of SARS-COV-2 and changes therein (Kraemer et al., 2020), examine how those changes have resulted from social distancing policies or recommendations (Kissler et al., 2020), and leverage these estimates to translate potential future policies into expected behavioral changes, and epidemiological models (Jewell et al., 2020). These analyses will be key in surveillance for leading behavioral changes that will affect the course of the COVID-19 epidemic. We organize the report around the following questions:

1. How have Coloradans modified their activity patterns in response to the COVID-19 epidemic?
2. How much of the change in activity is due to the state and local orders put in place for public health concerns?
3. How do the observed behaviors vary by (a) time; (b) age group; (c) location type; (d) administrative locations.

While overall patterns have changed, we also demonstrate the variability in those changes. Social distancing policies have been a primary tool to combat COVID-19. A previous report (Buchwald et al., 2020) estimates that Colorado residents have achieved a high level (as much as 75%) reduction of social contacts due to social distancing. Two previous interventions are key to identifying activity changes. Consistent with previous reports, we refer to these as “Phase 1” social distancing interventions, which included closing schools, bars, restaurants, and ski resorts on March 17. “Phase 2” indicates the statewide stay at home order, which was implemented on March 26 and expired on April 27. We indicate these dates on figures when the data is available.

How have Coloradans modified their activity patterns in response to the COVID-19 epidemic?

Mapbox's sensor-based activity data indicates that people in Colorado decreased activity since early March. Mapbox produces a summary activity index based on anonymized mobile device use in an area over time. There are roughly 30,000 points scattered across Colorado, though they are more concentrated in urban and suburban areas. We aggregate the activity index within a city to construct a city-level index and normalize that index to the mean activity index throughout January.

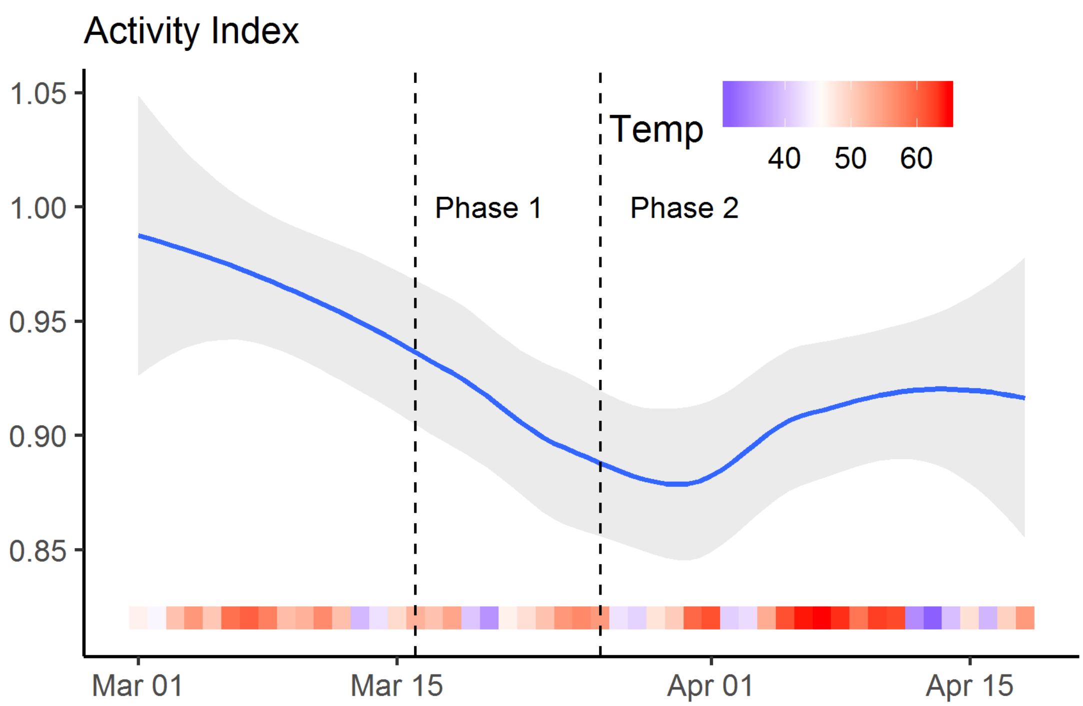


Figure 1. **Changes in Activity Index, Statewide, relative to January Baseline** (Source: Mapbox). The color ribbon indicates CO average maximum daily temperature (Fahrenheit). We omit the temperature scale in future figures because it remains constant.

Some variation in response is apparent across selected cities, reflecting differing demographics and geographies, in Colorado. While Denver, Silverthorne, and

Steamboat Springs have seen declining activity throughout March, the decline in Durango did not start until well into March. The decline in activity has been relatively slower in Fort Collins.

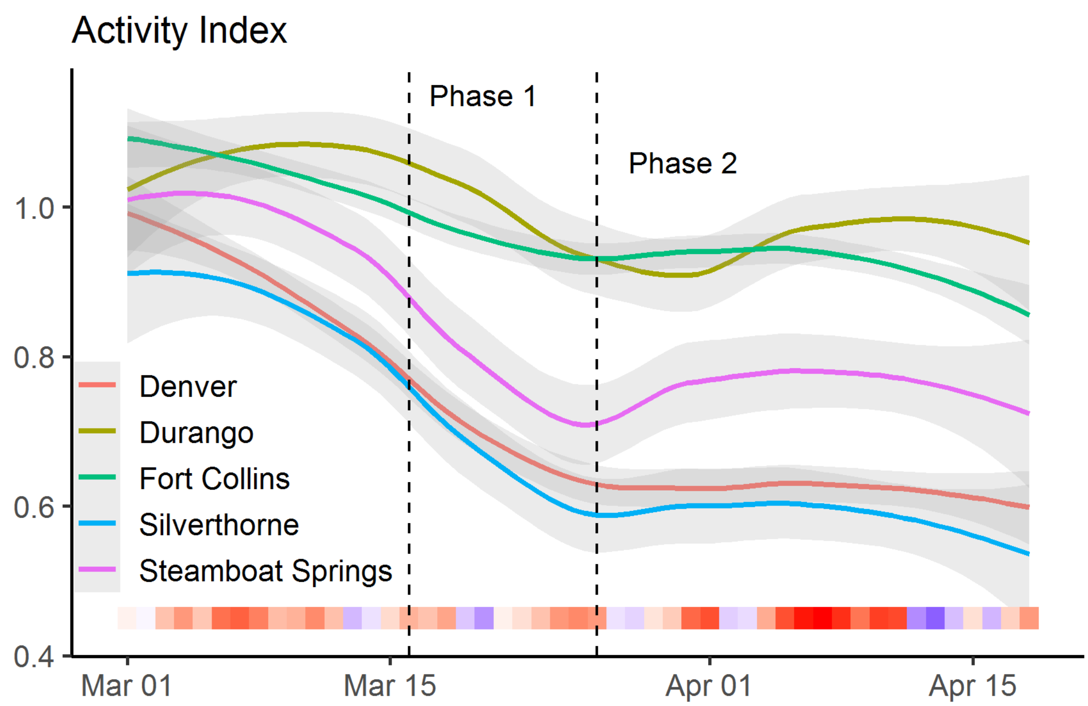


Figure 2. **Changes in Activity Index, City-Specific, relative to January Baseline** (Source: Mapbox). The color ribbon indicates CO average maximum daily temperature (Fahrenheit).

Time at Home

SafeGraph[2] is another mobile device data aggregator providing “point of interest” information from geo-fenced locations that are classified according to a range of location use types. Of primary interest following the social distancing interventions are the amount of time people spend at home, as compared to other locations where potentially transmitting social contacts could occur. SafeGraph reports the median time spent at home across all devices in a Census block group. Colorado Census block groups have an average population of 1500 (see appendix for more detail on the data).

[2] SafeGraph (www.safegraph.com), a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group.

Figure 3 shows the trend in time spent at home in Colorado since January 1. Coloradans generally begin to spend more time away from home as the weather warms. The figure shows that time spent at home had been increasing since the start of the epidemic in early March and was likely encouraged by the Phase 1 closures and Phase 2 stay at home order. However, the trend appears to change in mid-April. A decline of time at home does not necessarily imply that time is spent in locations of increased transmission risk. For example, people may take walks in their neighborhood or visit outdoor recreation sites. We investigate some of these possibilities below.

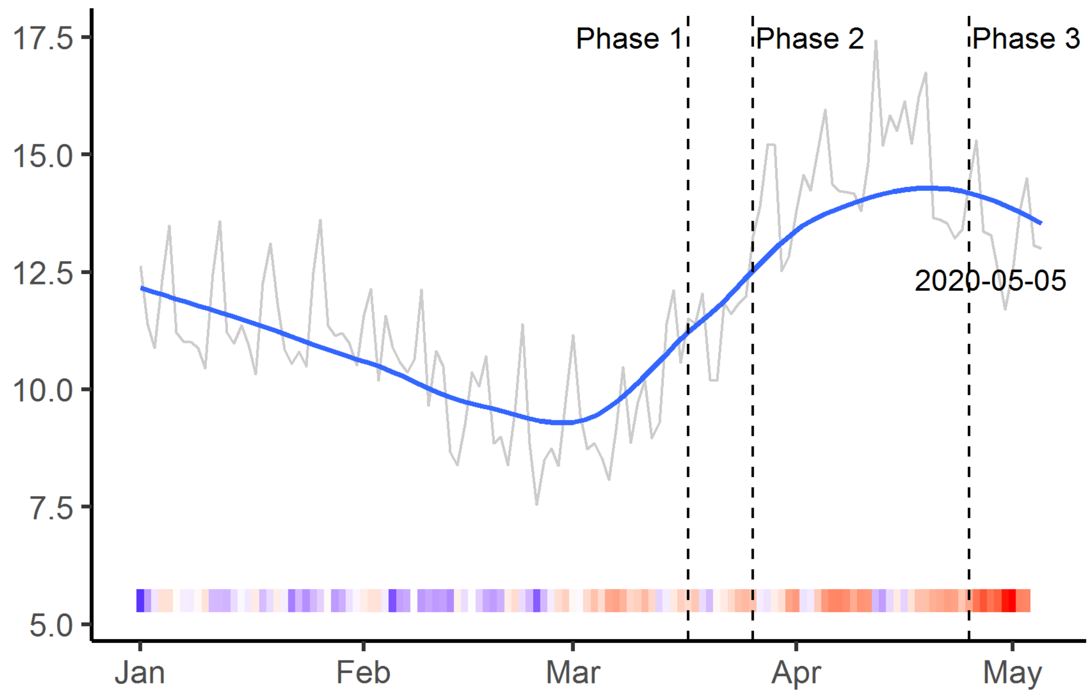
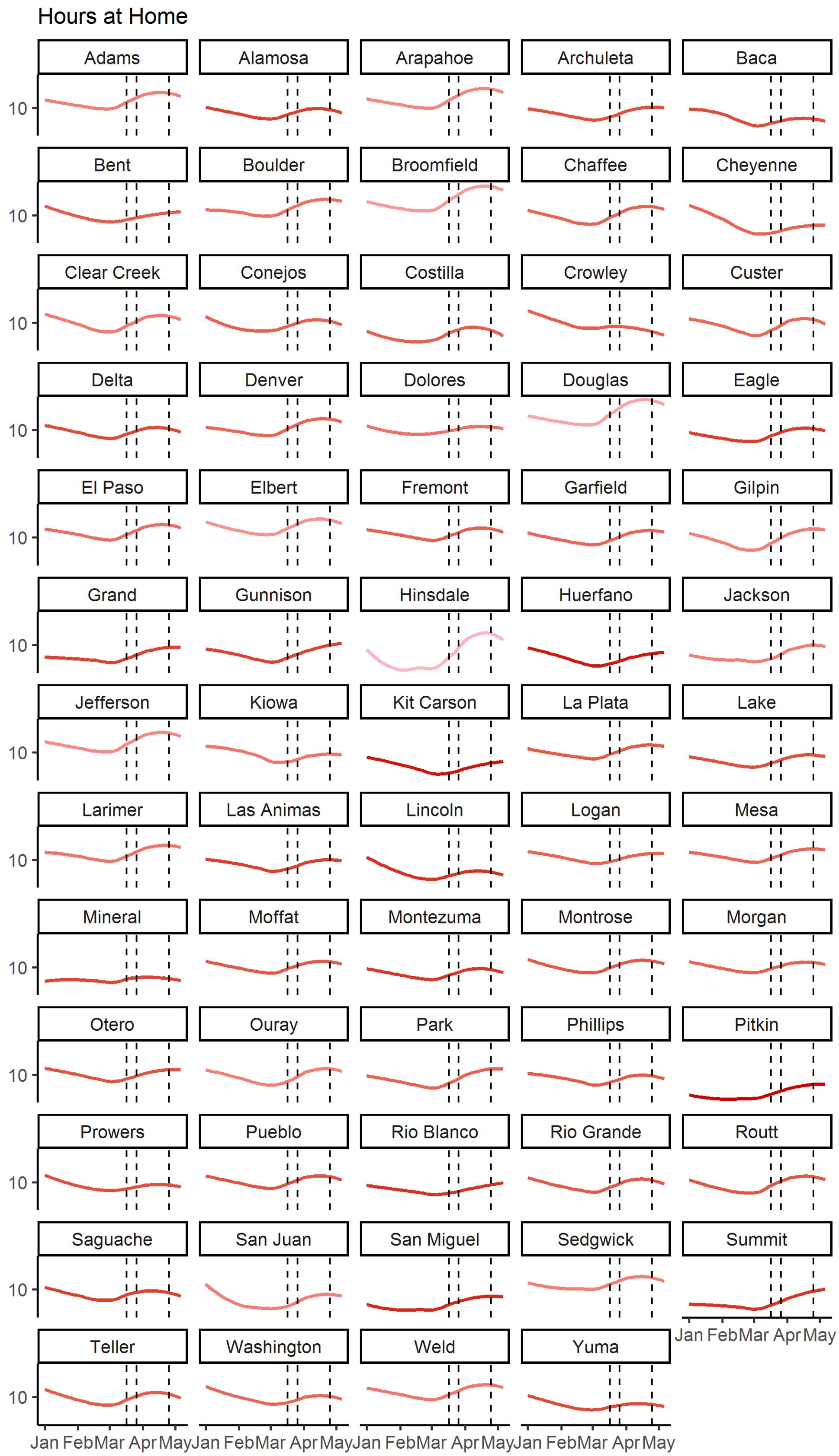


Figure 3. **State Average of Median Daily Hours Spent at Home** (source: SafeGraph). The gray line is daily average and the blue line is a smoothed trend. The color ribbon indicates CO average maximum daily temperature (Fahrenheit).

Variation by County

We now explore the variation in time spent at home across counties. The trend in most counties exhibits a "v" or "u" shape as behavior changed in response to the epidemic. While many counties have continued the trend of spending more time at home, some appear to be spending less time at home in recent days. SafeGraph has seen variation in the number of devices in their sample throughout the epidemic. We suspect that may influence the estimates in less populated counties more so than counties along the Front Range.



Hours at Home
Adams
Alamosa
Arapahoe
Archuleta
Baca
Bent
Boulder
Broomfield
Chaffee
Cheyenne
Clear Creek
Conejos
Costilla
Crowley
Custer
Delta
Denver
Dolores
Douglas
Eagle
El Paso
Elbert
Fremont
Garfield
Gilpin
Grand
Gunnison
Hinsdale
Huerfano
Jackson
Jefferson
Kiowa
Kit Carson
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Montezuma
Montrose
Morgan
Otero
Ouray
Park
Phillips
Pitkin
Prowers
Pueblo
Rio Blanco
Rio Grande
Routt
Saguache
San Juan
San Miguel
Sedgwick
Summit
Teller
Washington
Weld
Yuma
10
Jan Feb Mar Apr May

Figure 4. **County-level trends in time spent at home**. (Source: SafeGraph) The darker red lines indicate lower time spent at home on the last day of the sample.

Variation by Demographics

SafeGraph provides anonymized data aggregated to the Census block group, so we do not have demographic information about individual mobile device owners. However, the American Community Survey collects detailed demographic and socioeconomic information, reported at the Census block group. We estimate a series of statistical models to associate the demographic information about the Census block group with trends observed in the mobile device data (see appendix for more detail). Figure 4 displays the trends in time spent at home by age group roughly corresponding to those used in the epidemiological model. Children are not represented in the mobile device data, so we exclude the population less than 15 years old.

The results suggest that while all populations have increased their time spent at home since early March, Census block groups with younger populations have responded the least. Areas with senior populations have increased their time spent at home, but not as much as people between 30 and 59 years old. The large adjustment by 30-59 group is likely driven by obligations to work from home and childcare.

Importantly, these models do *not* directly capture individuals' behavior changes. Instead, each curve represents the changes in behavior within census block groups with a higher concentration of residents of the specified age groups, as presented in each respective curve (see Appendix for precise interpretation).

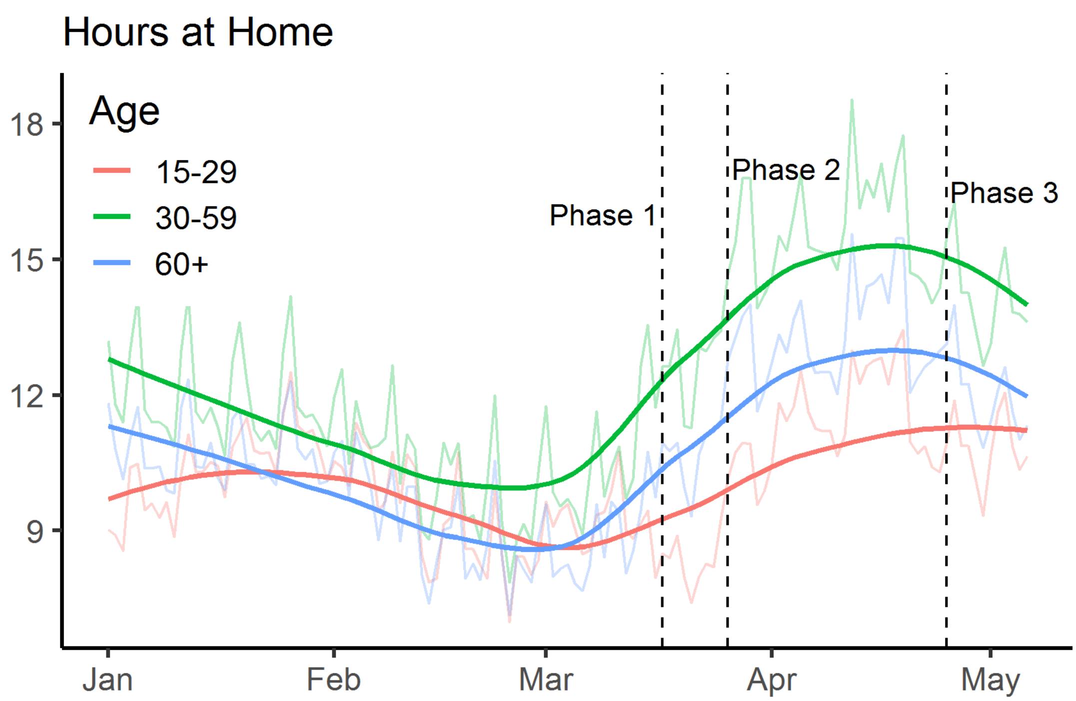

Figure 5. **Time Spent at Home by Age Groups** (Source: SafeGraph). The curves represent the time spent at home attributable to having more people in one of the three age groups.

Figure 6 displays the results of a similar analysis, but for household income categories. First, the trends suggest that people in all household income categories increased time at home. Second, there is variation in response across categories. Areas with higher proportions of less than $25k appear to reduce mobility the least whereas households with income above $100k spend the most time at home. These trends may reflect several important factors: people in higher-income households likely have more flexibility to work from home (Mongey et al., 2020), people in lower-income households are more likely to be employed in essential industries, and the residents of lower-income households may also be experiencing higher rates of job loss. Further analysis is needed to disentangle these impacts, and the patterns will likely change over time as unemployment rises.

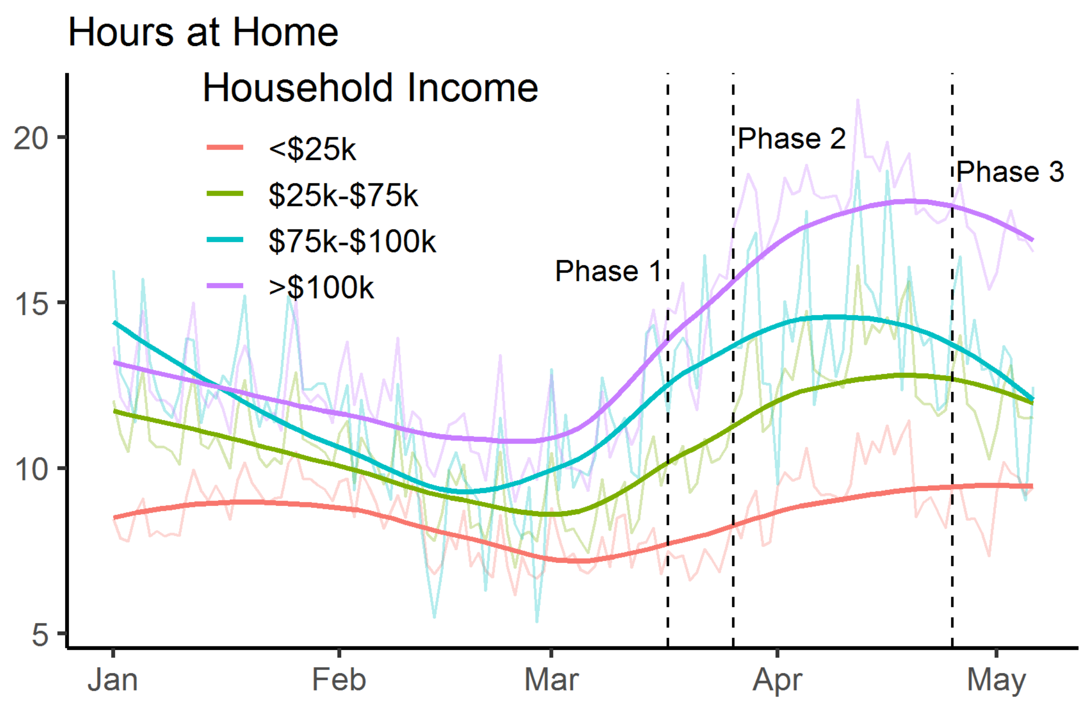

Figure 6. **Time Spent at Home by Age Groups** (Source: SafeGraph). The curves represent the time spent at home attributable to having more people in one of the four household income categories.

Time away from home

While time spent at home is one measure of response over time, people who do leave home may not be spending time in risky locations. Figure 7 shows the time spent *away* from home. The figure shows that the statewide average of median time spent away from home has fallen from over two hours to less than one hour per day. The regular fluctuations in the data (gray lines) are due to weekly work patterns. These weekly fluctuations are substantially reduced after social distancing begins. Figure 7 shows that time away from home decreased in March, but has begun to increase during the second half of April. The trends suggest that time away from home fell by approximately 60%, which is similar to the measure of social distancing estimated in the epidemiological model.

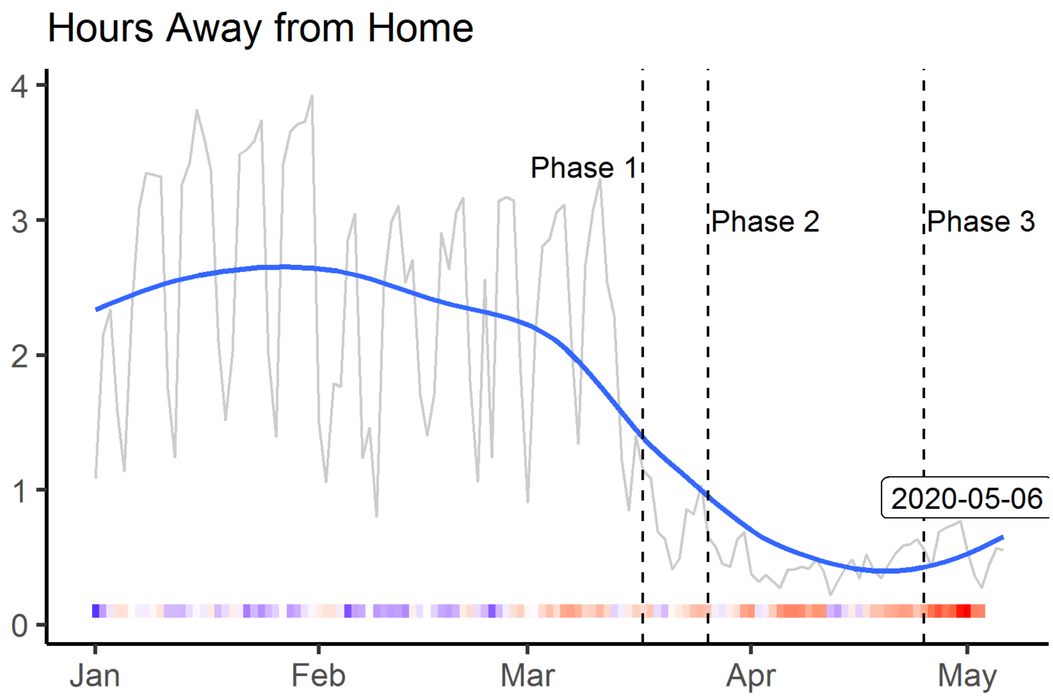

Figure 7. **Median Daily Hours Spent Away from Home** (source: SafeGraph). The color ribbon indicates CO average maximum daily temperature (Fahrenheit). The date indicates the last day data is available.

Points of Interest

SafeGraph also reports visitation to points of interest (POIs) across the state. These POIs include businesses as well as locations like parks near urban areas. Visitation patterns to these POIs are significant from a public health perspective because they are likely locations of transmission. The following figures display visitation trends in select POIs in select counties across Colorado. Trends for additional POIs and counties are available upon request.

Figure 8 shows the trend in daily visitation to Grocery Stores in Denver, Eagle, Larimer, and Mesa counties. We highlight these counties because they represent different areas of the state. The measure of daily visits is the fraction of mobile devices in a county that visit a grocery store. The results suggest that visits to grocery stores initially increased as people prepared to stay home, and then began to decline towards the end of March. Visitation has continued to rise through April, even exceeding the early March trends in Mesa county.

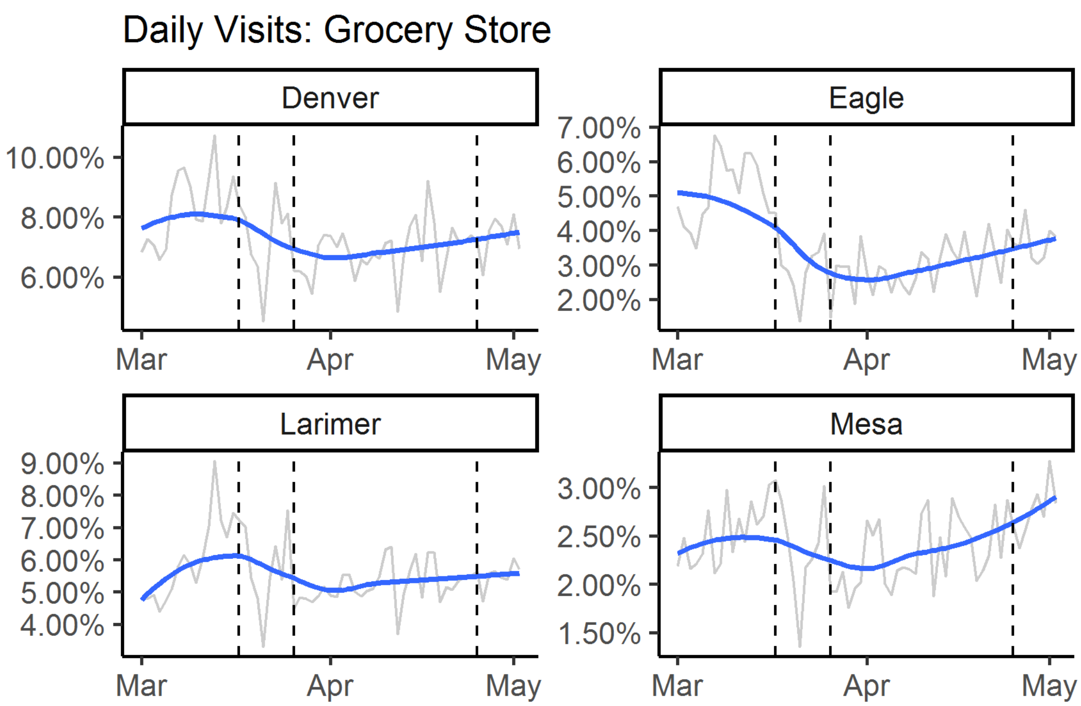

Figure 8. **Visits to Grocery Stores** (Source: SafeGraph). Fraction of mobile devices in a county that visit a grocery store by day. The dashed lines indicate the Phase 1, 2, and 3 orders.

The state orders have encouraged the residents of Colorado to reduce time in public locations. As the weather warms, people are likely to spend more time outdoors. The SafeGraph data include parks within a category of POIs called Museums, Historical Sites, and Similar Institutions. These figures may include other locations, especially in Denver County. The parks that are included are likely located near urban areas (e.g., city parks). Figure 9 suggest that visitation declined after the orders. However, there did appear to be a slight increase in visitation after the Phase 2 orders in Larimer and Mesa Counties. Park visitation has continued to rise after the announcement that the Phase 2 order would be relaxed.

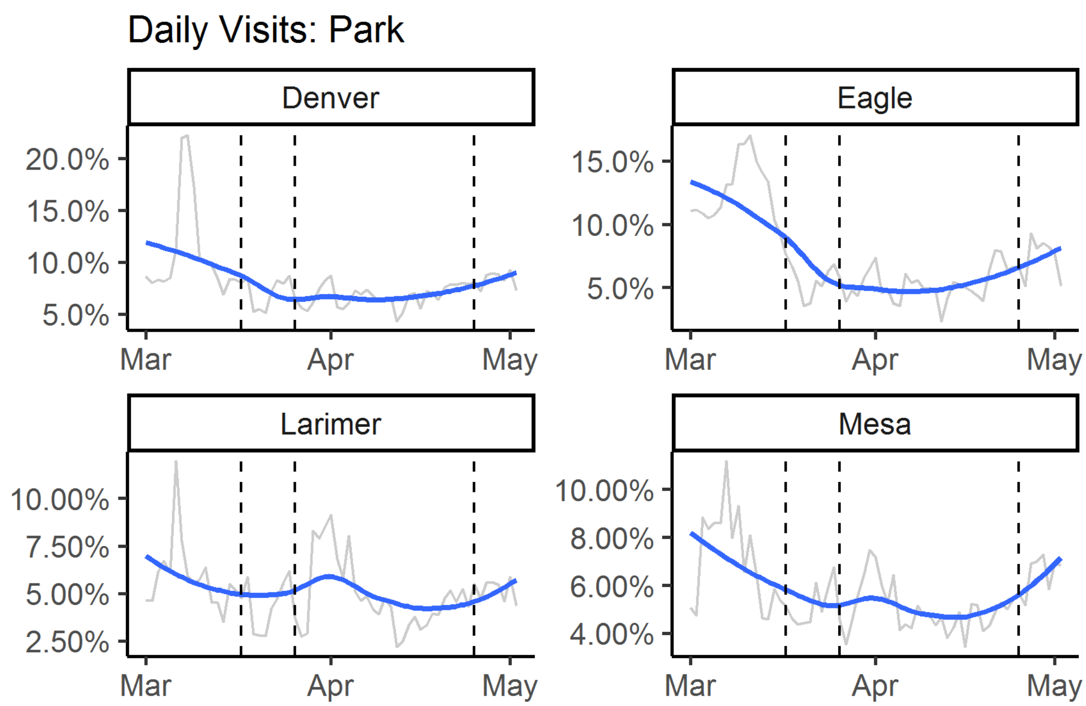

Figure 9. **Visits to Parks (and Museums and other sites)** (Source: SafeGraph). The fraction of mobile devices in a county that visit Museums, Historical Sites, and Similar Institutions by day. The dashed lines indicate the Phase 1, 2, and 3 orders.

Restaurants have experienced a significant decline in visitation, which reflects the closure of many operations. Figure 10 shows the decline in visitation to restaurants in select locations across the state. In Eagle County, restaurant visitation is likely driven by travelers to and from the mountains, which declined from 75% at the beginning of March to almost nothing by the end of March. Visitation in other counties may be driven by take-out orders.

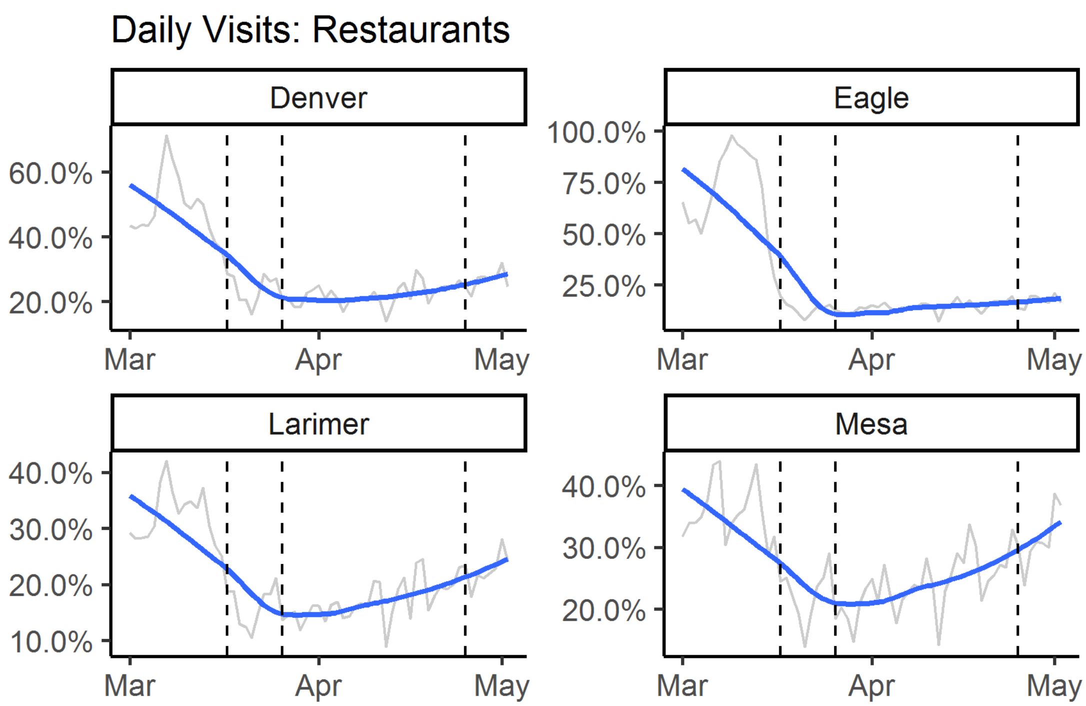

Figure 10. **Visits to Restaurants** (Source: SafeGraph). The fraction of mobile devices in a county that visit a Restaurant by day. The dashed lines indicate the Phase 1, 2, and 3 orders.

As with restaurants, many personal care service businesses suspended operation. These businesses include barbershops, nail salons, etc. Figure 11 displays the declining trend in visitation to personal care businesses throughout the month of March. However, visitation has begun to rise during the last part of April.

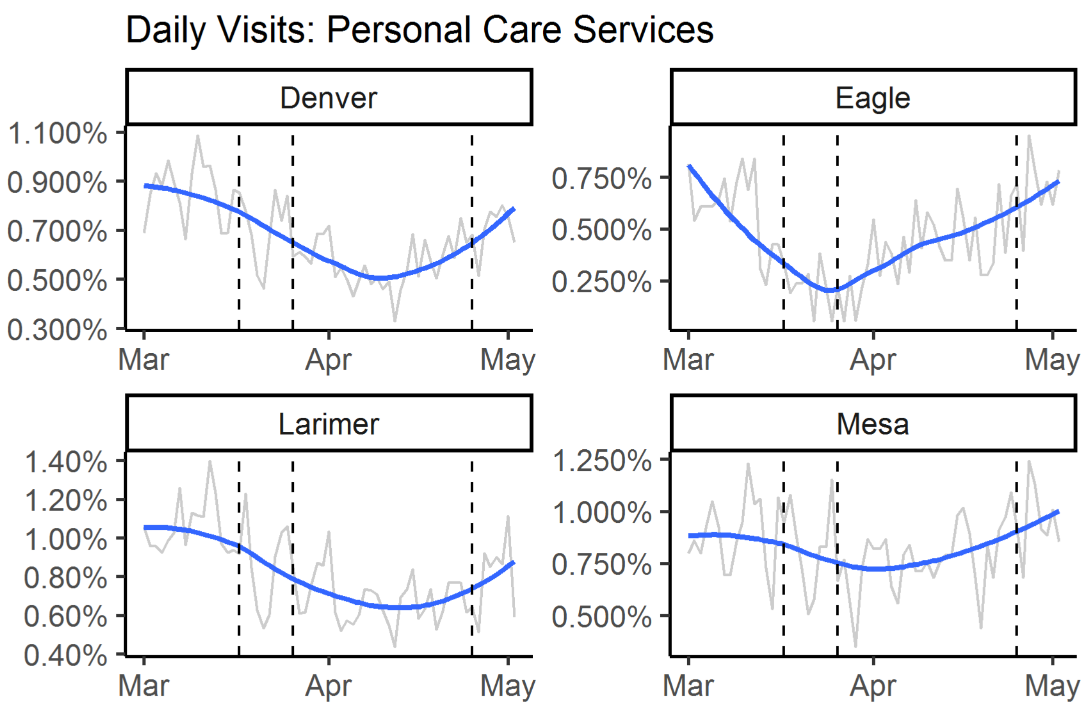

Figure 11. **Visits to Personal Care Services** (Source: SafeGraph). The fraction of mobile devices in a county that visit a Personal Care Services by day. The dashed lines indicate the Phase 1, 2, and 3 orders.

Data Privacy Precautions

Many of the mobility pattern datasets analyzed in this report were based on a data-secure warehouse maintained by the Colorado Innovation Response Team, led by Parker Jackson. An important caution for using any such data, even while many have advocated for the use of mobility data for better contact tracing of the pandemic (Buckee et al., 2020), any such analyses must wrestle with the protection of subject privacy (Horvitz and Mulligan 2015). In particular, a key risk is the re-identification of an individual based on ostensibly anonymized data (Poor and Davidson 2018), a concern particularly shared among the general public (Knight 2020). When such identification occurs, it is referred to as an adversarial attack. While we deal with anonymized digital mobile device data in this report, similar issues of re-identification have been brought up in the context of genetic (Gymrek et al., 2013) and social network data (adams 2019; Rocher et al., 2019). These considerations are especially important in light of the myriad proposals to incorporate some form of digital enhancement to contact tracing approaches, as test, trace, and isolate strategies become a central component of any relaxation of social distancing recommendations (Greenwood et al., 2020).

Here, to ensure these protections, we employ two primary strategies. The primary analytic approach to protecting privacy is reporting aggregation. Our analyses are all presented in aggregate form, with the type of aggregation depending on the particular question. We aggregate variably by geographic region, demographic group, and types of activities. All the figures shown in the report have relied on the aggregation of some sort. In the data privacy literature, if the number of observations over which to aggregate is too small, then we omit those results. Our other primary protections arise from the ways the data were gathered and analyzed. First, we rely on "point of interest" analyses that focus on the number of people (or devices) that pass through certain location fences within specified time periods, and these locations are not linked to one another. Second, all of the data collection platforms in use have opt-out options. We cannot access any data for those devices where people have chosen to opt-out (e.g., by turning off location tracking on their mobile device).

We particularly note that in the time at home analyses (Figure 3), the information we have is that mobile devices are within a certain `fence.' In each of the figures used here, we are relying only on the aggregated information, and nothing was accessed at the device level (i.e., we do not have the ability to identify which home 'fences' are represented). Moreover, currently, we are only using data captures of devices within any single fence; i.e., there is no tracing of sequences of individual devices across locations, something that would potentially make individual people identifiable. Additional computational safeguards in terms of data security, and proper data governance structures with citizen stakeholders as representatives are necessary for any approaches moving forward that would rely on more precise device-level information.

Future Applications

Thus far, we have primarily documented how mobility patterns have changed in light of the COVID-19 responses' recommended social distancing practices. In addition to documenting these patterns, the types of changes described above can also be used to improve the modeling of disease transmission processes, and the effects of any interventions on those dynamics (Benzell et al., 2020).

Social contact patterns drive the transmission potential of SARS-COV-2 through a population (in terms of the SEIR epidemic modeling approach used by our team (Buchwald et al., 2020)). This is one of the primary drivers of how the model determines the rate at which susceptible individuals come in contact with those who are infectious), and "social distancing" policies attempt to alter both the extent and structure of those patterns (Prem et al., 2020). Considered as a single measure, we can estimate the volume of social contacts an individual has that provide the potential for transmission, and assess the effects of interventions (whether based in governmental orders, recommendations, or voluntary changes) on how many such contacts occur between people in a population (Martin-Calvo et al., 2020). This approach focusing only on the volume of such social contacts assumes what is known as “random mixing” - which denotes that the likelihoods of any pair of people within the population coming into contact with one another are equivalent (Burr and Chowell, 2008).

There are a variety of ways to estimate social contact patterns that would facilitate potential viral transmission. An empirical approach used previously in modeling H1N1 relies on individual time-use diaries to derive estimates of the mixing patterns in such contacts (Bayham et al., 2015). While these approaches can provide estimates of contact patterns from samples with well-understood sampling properties, and are therefore useful for estimating general contact patterns in typical circumstances and/or when they become available in retrospect, they do not provide the “real-time” updating needed to identify changes as they take places during a pandemic where changes are happening rapidly. The types of “real-time” data described above would allow for a closer representation of how those mixing patterns respond to social distancing measures, account for how any such changes are differentially patterned across different locations or activities, and/or be combined with other characteristics (e.g., sociodemographic) to account for and project how the changes in those mixing patterns differ across subgroups.

One example where this combination could be particularly helpful is for social distancing recommendations that apply differentially to location types (e.g., partially opening workplaces, but not bars), and encourage different changes by different subsets of the population (e.g., encouraging those over a certain age or with particular comorbidities to maintain stricter reductions in social contacts). In those cases, we can both pick up who different subgroup-location combinations actually alter contact rates, and we can allow for differential uptake of new interventions across groups - e.g., when some groups’ contacts necessarily go up (e.g., by returning to their workplace), accounting for others’ counterbalancing maintenance of low levels of social contacts (e.g., for those who can continue to telecommute; this is an explicit part of the “reduced workforce” element of Governor Polis’s recommendations in the “Safer at Home” approach that took effect upon the expiration of the “stay at home” order).

Conclusion

For public health, the most critical application of these new approaches will be for surveillance for behavior changes that will increase risk for transmission. With the “Safer at Home” approach, Colorado is embarking on the slow path towards normalcy. We do not want to wait for rising numbers of critically ill people to signal that social distancing has increased too much and that the other epidemic control measures are not as effective as assumed. Monitoring behavior across Colorado and across all groups within its population will be a critical element in an “early warning” strategy. In this report, we show that the needed data and methods are available, although appropriate caution is needed to assure that privacy is protected.

Methods Appendix

This appendix provides additional detail to analysis referenced in the main text.

Data

We use mobile device data from two sources: Mapbox and SafeGraph. Mapbox reports an activity index for approximately 30,000 points around Colorado based on mobile device usage. SafeGraph (www.safegraph.com) aggregates anonymized mobile device data and provides two products. The first is a dataset called Social Distancing Metrics (SDM) designed specifically for understanding movement patterns during the COVID-19 epidemic. The second dataset includes visitation data to over 100,000 points of interest in Colorado (e.g., a particular Walmart). We integrate daily temperature data from gridMET (Abatzolgou, 2013).

We use the Social Distancing Metrics to document broad trends in where people are spending time. The SDMs are aggregated to the Census block group level. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. We use two key metrics: the median time spent at home of all devices within a Census block group, and the median time away from home of all devices within a Census block group. We aggregate these block group measures up to the county by calculating the mean of the values of all census block groups within a county. Since the distributions of time at home and time away from home are not symmetric, the median aggregations imply that the two measures do not sum to the total time in a day.

Demographic Analysis

All data is anonymized, so we have no information about individual demographics. However, the variation in behavior by demographics is relevant to understanding public health impacts. We associate the time spent at home metric with aggregated demographic information reported in the American Community Survey run by the US Census. There are over 3000 census block groups in Colorado with an average population of just over 1500. We classify each census block group as dominated by one of three age categories: 15-29, 30-59, and 60+ if the fraction of the population in one of those categories exceeds 70%. The daily estimate of time spent at home by the age group is the average of the census block group's *median home dwell time* with a dominant population. Not all census block groups have a dominant population, so these estimates are based on a subset of the sample. The results are robust to thresholds between 60% and 80%.

Analyses of mobile device data rely on representative samples of the population. Future research is need to ensure that the people represented by the mobile device data are indeed representative of the entire population. Otherwise, inference may be misguided.

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