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The association between smartphone-derived population-level mobility and COVID-19 in 2020: a census tract-level analysis of King County

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Abstract

The association between smartphone-derived population-level mobility and COVID-19 in 2020: a census tract-level analysis of King County

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Stay-at-home orders were an important tool in mitigating the COVID-19 pandemic. This ecological study used small area estimation models to estimate the associations between mobility and social vulnerability with COVID-19 case counts under different lockdown conditions for all 397 census tracts in King County, Washington in 2020. Data was used from Safegraph's Social Distancing Metrics dataset, King County's COVID dashboard, and American Community Survey data. Census tracts with higher mobility and increased social vulnerability were more likely to have higher numbers of COVID cases, especially as the county entered into their reopening plan. In early months of the year the association was stronger in northern tracts, particularly around the Seattle and Eastside areas. In later months, the southwestern tracts had a stronger association. This spatial analysis illustrates the many factors that influence higher transmission in certain areas, as well as the need to address geographic inequalities and fine tune public health response appropriately.

INTRODUCTION

Stay-at-home or lockdown policies are based on the idea that if people stay home, COVID-19 transmission and cases will subsequently decrease. However, whether these policies were adhered to and their effects on COVID case numbers over the course of the pandemic is only beginning to be explored.[1–5] Mobility data in the form of call detail records, air travel, and transportation data have previously been used for surveillance and modeling transmission of infectious diseases.[6,7] However, as technology has become more integrated into individuals' daily lives, smartphones have become a new source of information and data that may be useful for public health purposes.

A global pandemic requiring implementation and adoption of non-pharmaceutical interventions has never occurred in the age of the smartphone. Global positioning system (GPS)-based smartphone mobility data is as a novel way to monitor adherence to social distancing in the face of the COVID-19 pandemic. As governments implemented stay-at-home and lockdown orders, technology companies such as Facebook, Google, and Apple and data companies like Safegraph, Cuebiq, and Unacast began releasing aggregated mobility datasets to aid researchers and public health decision-makers. Leveraging these "big data" sources in a public health crisis has presented an unprecedented and unique opportunity for technology to be used to help mitigate the pandemic.[8] Some research organizations have used these data sources to create social distancing dashboards or study relationships between other variables like political party with mobility.[9] The CDC and various cities governments have utilized these data to inform decision-making around reopening and evaluate the effects of their policies.[3,10] Others have been critical and wary of the ethical and privacy implications of these types of data.[11]

Studies have shown sharp decreases in mobility after state lockdown orders, but whether these drops in mobility lead to lower case counts on a more local level remains to be seen.[2,12] Both mobility and disease transmission are complicated phenomena. Mobility is affected by many different factors on an individual level, such as occupational type, housing situation, and perceptions and beliefs about COVID-19, and disease transmission is affected by community transmission levels, individual behaviors, and individual innate vulnerability. Most studies so far examine the effectiveness of reduced mobility on

COVID-19 transmission on a state or county level, but have not been used for more local data.[13,14] In addition, COVID has disproportionately affected vulnerable communities, and many in these communities may have seen their mobility differently affected by stay-at-home orders.

This paper explores the value of using location tracking data collected from smartphone applications for public health purposes, as well as factors that contribute to higher risk of COVID-19. This study aimed to describe spatial trends and assess the associations between population mobility and social vulnerability with COVID-19 case counts in King County's 397 census tracts at different times during 2020.

METHODS

In this ecological study, we used small area estimation models to estimate the association between mobility and COVID-19 case numbers under different social distancing and lockdown conditions for all 397 census tracts in King County, Washington. The study time period included 11 months (end of January 2020 through the end of December 2020). Multiple data sources were used in this analysis: local COVID case data, mobility data from smartphones, social vulnerability scores from the CDC, and American Community Survey data. Each data source is described below.

COVID case data were obtained from King County's daily COVID-19 outbreak summary database from the "Biweekly counts and rates by geographic levels" dataset.[15] Data were provided biweekly by census tract, ZIP code, health reporting area, and city and includes counts and rates of people tested, all test results, COVID test positives, hospitalizations and deaths. The positive case count variable, the outcome for this analysis, is defined as the count of unique King County residents who have had a confirmed positive COVID-19 PCR lab result reported to the Washington State Department of Health.

Mobility data were extracted from Safegraph's Social Distancing Metrics datasets. These data were collected via pings to applications on users' smartphones that opt into location tracking.[16] Approximately 90,000 to 100,000 devices in King County are included in the dataset per day, which represents about 4.4% of the total county population.[17] Data are aggregated to the census block group level and differential privacy is applied to device count metrics by Safegraph before being made publicly available. Data were aggregated up to the census tract level by summing counts of devices within census block groups. Studies of sampling bias have shown that there are high correlations between Safegraph data with census data for various demographic and geographic factors.[18] A device's home location is determined by the common nighttime location within 153m x 153m over a 6 week period. The measures "devices completely at home" and "device count" were used to determine the proportion of devices in each census tract that remained completely "at home." The proportion of devices that did not stay completely at home was used as a proxy for mobility for this analysis.

The Social Vulnerability Index (SVI) is a composite variable that quantifies resilience of communities to external stressors on human health, such as disease outbreaks, and is calculated for each census tract in the US by the CDC.[19] This score is calculated using 15 census variables in four categories: socioeconomic status, household composition, race/ethnicity/language, and housing/transportation. Washington state SVI scores were calculated by the CDC using 2018 American Community Survey data.

Number of positive COVID cases and percent of devices not staying completely at home were aggregated to time blocks based on the lockdown or social distancing policies in effect in King County and Washington state (Table 1). The first time period serves as a baseline, from January until the Governor's *Stay Home, Stay Healthy* order began in Washington state.[20] The next period encompasses the entirety of the original Stay Home order from March until May. The next two time periods include King County's transition into Phase 1 and Phase 2 of the Safe Start reopening plan during the summer. The last time period begins when new restrictions were enacted statewide in November through the end of the year. A 10-day time lag was used to account for the presumed incubation period between mobility and receiving a positive test result.[1]

Small area estimation methods were used to provide more reliable counts from small areas like census tracts. These allow models to "borrow strength" from surrounding areas and provide more accurate estimates, based on the idea that adjacent areas are more likely to be similar.[21] The Besag-York-Mollie (BYM) model includes a term that accounts for spatial autocorrelation as well as a term for ordinary random-effects that captures non-spatial heterogeneity.[22] A BYM model was run for each time block, assuming that the observed counts of positive COVID-19 cases follow a Poisson distribution

$$Y_i \mid \theta_i \sim P_O(E_i \times \theta_i), i = 1, \ldots, n,$$

where E_i is the expected count and θ_i is the relative risk in census tract i. The logarithm of θ_i represents

$$\log(\theta_i) = \beta_0 + \beta_m x_m + \beta_{SVI} x_{SVI} + u_i + v_i$$

where β_0 is the intercept, β_m is the coefficient of the mobility covariate, β_{SVI} is the coefficient of the social vulnerability covariate, u_i is a structured spatial effect, and v_i is an unstructured spatial effect. Models were fitted with the integrated nested Laplace approximate (INLA) package in R version 4.0.3.[23,24] As these data are not individually identifiable and COVID case data from the county are designated as public health surveillance, this project was not considered human subjects research and did not require full Institutional Review Board review by the University of Washington.

RESULTS

King County experienced three peaks in COVID cases during spring, summer, and again in the winter 2020, with the wintertime peak much higher than either of the previous peaks. The maximum number of new cases per day in King County was 968, occurring in December (Figure 1, panel B). From February 2020 to the end of December 2020, King County reported a total of 62,172 positive cases.

Mobility was high in February and early March 2020, with a steep decline in mid to late March as cases began to increase in Washington (Figure 1, panel A). Mobility decreased significantly even prior to the statewide stay-at-home orders, as public health leadership and many large corporations encouraged people to start working from home and canceling large gatherings. The maximum proportion of devices leaving their homes at least once per day during the observation period was 81%, which occurred in February and early March. The period of time with the lowest overall mobility was during the *Stay Home,* *Stay Healthy* order in late March through early May, during which time an average of 48% of devices left their home area. In the months following the original stay-at-home order, mobility slowly began to increase to around 65% in July and remained around this level for the remainder of the year.

Social vulnerability is ranked by percentile, with a ranking of 0.9 indicating that 90% of the census tracts in the state are less vulnerable than that tract. Social vulnerability varies greatly within King County (Figure 2). The median SVI in the county is 0.36, however, the minimum is 0.0007 and the maximum is 0.996. Census tracts in southwestern King County are more vulnerable, while tracts in the Seattle and eastern King County areas have indices of less than 0.2, making them less vulnerable than the rest of the county and state. The most vulnerable tracts are further inland from Puget Sound and Lake Washington, with tracts adjacent to the water being less so.

While there was no statistically significant relationship between mobility and positive case counts during the early phases of the pandemic, the association became significant during Phases 1 and 2 of the Safe Start reopening plan, and during the fall of 2020 (Figure 3). During Phase 1 of the Safe Start plan, holding SVI constant, if 100% of devices in each tract did not stay at home, our model would predict an average 11-fold increase in positive COVID cases (95% CrI 3.4, 38). Increased social vulnerability was associated with higher COVID case positivity in every time period. The summer months of the Phase 1 reopening plan also saw the strongest associations for SVI. Holding mobility constant, for every 1 percent decrease in SVI (where decreased SVI score implies increased vulerabulity), estimated positive COVID cases increased 9.5 times (95% CrI 7.74, 11.7).

Relative risk of COVID-19 case counts in relation to mobility varied greatly depending on location within King County (Figure 4A-E). Lighter census tracts indicate lower relative risks, while darker blue tracts represent areas where the relative risk is stronger. In early 2020, highest relative risks were found in northern census tracts of King County, around the Seattle and

Eastside areas that included some of the first known cases in the United States. During the initial Stay Home, Stay Healthy order, risk was more evenly distributed throughout various tracts throughout the county. However, during the latter parts of the year, starting from Phase 2 of Safe Start, the southwestern tracts of King County were disproportionately at risk. For example, during the last two months of the year, census tracts in Kent had relative risks between 1.44 and 3, whereas tracts located in Seattle, Kirkland, and Bellevue had relative risks lower than 1.

DISCUSSION

This ecological census tract-level analysis used small area estimation to model the relationship between smartphone mobility levels, social vulnerability, and COVID-19 cases during different time periods in King County. Mobility and social vulnerability were both found to be independently associated with COVID case counts in Phases 1 and 2 of the Safe Start reopening plan through the remainder of the year. The strongest relationship was found during Phase 1, during May and early June.

This finding of stronger associations during phase 1 may be due to warmer weather and the allowance of outdoor recreation increasing mobility and socialization. A statewide mask mandate was implemented July 7, in the middle of Phase 2, which might explain why the association was slightly weaker overall during this phase, as people were taking more protective behaviors like masking while leaving their homes.[25] However, it should be noted that the credible intervals were still quite large, likely because these time periods were shorter than the others.

Social vulnerability was associated with higher COVID incidence during every time period examined except for the pre-pandemic months. This is consistent with other findings that show that areas with high proportions of vulnerable populations have higher incidence of COVID-19.[26–28] These populations include non-white Hispanic and Black populations, as well as neighborhoods with higher levels of poverty. SVI is a composite measure and includes not only race, ethnicity, and poverty level, but also other factors that may contribute to higher incidence of COVID-19 including crowded housing, lack of vehicle access, and high percentage of non-English speaking residents. These indicators may make it more difficult for people to socially distance or isolate or access information and resources. These results are also consistent with spatial analyses of Chicago and Boston that have identified higher COVID-19 incidence in more vulnerable and disadvantaged populations.[29,30]

This analysis shows the importance of examining how mobility affects COVID cases on a more granular level, and how statistical methods can be used to do so. Although on average there is a strong relationship between the mobility and COVID-19 countywide, some census tracts have much higher relative risks of COVID while others have an inverse association. Simply looking at the county as a whole, especially diverse and densely populated urban counties like King County, may mask some of important geographical variation. Previous analyses using Safegraph data have compared King and Yakima counties in Washington and found a negative association between time spent at home and transmission in both areas, however, differences in income and occupational categories drove higher transmission in Yakima.[31] As Yakima has a higher proportion of jobs that are impossible to do from home (e.g. agriculture), Washington state may consider geographic variations in stay-at-home policies, and also reinforces the need to rely on a variety of tools and mitigation measures early on in a pandemic response.

Our study had numerous strengths, including the use of fine-grain mobility and a small-area estimation technique that can account for small populations. However, our results should be viewed in light of several key limitations. First, sampling bias is unavoidable when using smartphone data. Although smartphone ownership has increased over recent years to 85% in the US, smartphone ownership remains slightly lower in those 65 and older, those with lower incomes, and lower levels of education.[32] Safegraph only collects data from users who have opted-in to location tracking via apps on their smartphone. Names of the apps are not disclosed, so their user base is entirely unknown. Furthermore, those who may be distrustful or wary of location tracking may have different behaviors and beliefs about, mobility, COVID-19 risk and protective behaviors. A recent study of Safegraph's validity found that older and nonwhite Americans were less likely to be captured by mobility data.[33] This may be an important limitation for this analysis since older and nonwhite Americans have been at higher risk for COVID-19.[34–36] Additionally, this analysis relies on the assumption that one smartphone is equivalent to one person, and that individuals take their smartphones with them every time they leave their homes, however, this may not always be the case for households that may share devices or for those who do not always have their device with them. As others have cautioned, it is important to understand the limitations of smartphone data and how they may influence the conclusions that can be drawn from them.[37,38] This analysis also relies on reported case counts, which may be underreported due to limitations in testing.[39] Differential testing behavior and availability may also contribute to underreporting of cases, for example, Hispanic-majority areas have been found to have significantly lower testing rates but higher case rates than White-majority neighborhoods, which may make risk in vulnerable areas seem higher.[27]

Human behavior, including mobility and travel, is an important driver of infectious disease transmission. Smartphone mobility data has potential to be used in the future for not only understanding COVID-19, but also other diseases like influenza. Understanding responses to major non-pharmaceutical interventions such as stay at home and lockdown orders is important to determining their value, and how to better implement them in the future. Mobility data may be useful for public health to improve their understanding of locations where people are less willing or able to comply with stay-at-home orders and to aid these communities in other ways, for example, through increased testing or providing free masks or sanitation supplies. Incorporating social determinants of health and understanding how to help vulnerable populations become less vulnerable should be a priority. Even independent of the COVID-19, efforts should be made to address geographic inequalities and fine-tune public health response and preparedness efforts based on local variation in order to improve countywide health.

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Tables and Figures

Table 1. Washington and King County COVID-19 mitigation policies throughout 2020

Time Block	Dates	Policy	Description
1	Jan 11 – March 23	Pre-pandemic	No restrictions
2	March 23 – May 5	Stay Home, Stay Healthy Order	Stay home unless pursuing essential activities, no gatherings, all businesses except essential ones must close
3	May 5 – June 19	Safe Start Phase 1	No gatherings, some outdoor recreation permitted
4	June 19 – Nov 16	Safe Start Phase 2	Outdoor activities with <5 outside household allowed, limited retail and restaurant reopening capacity
5	Nov 16 – Dec 31	Fall restrictions	No indoor gatherings, dining, fitness

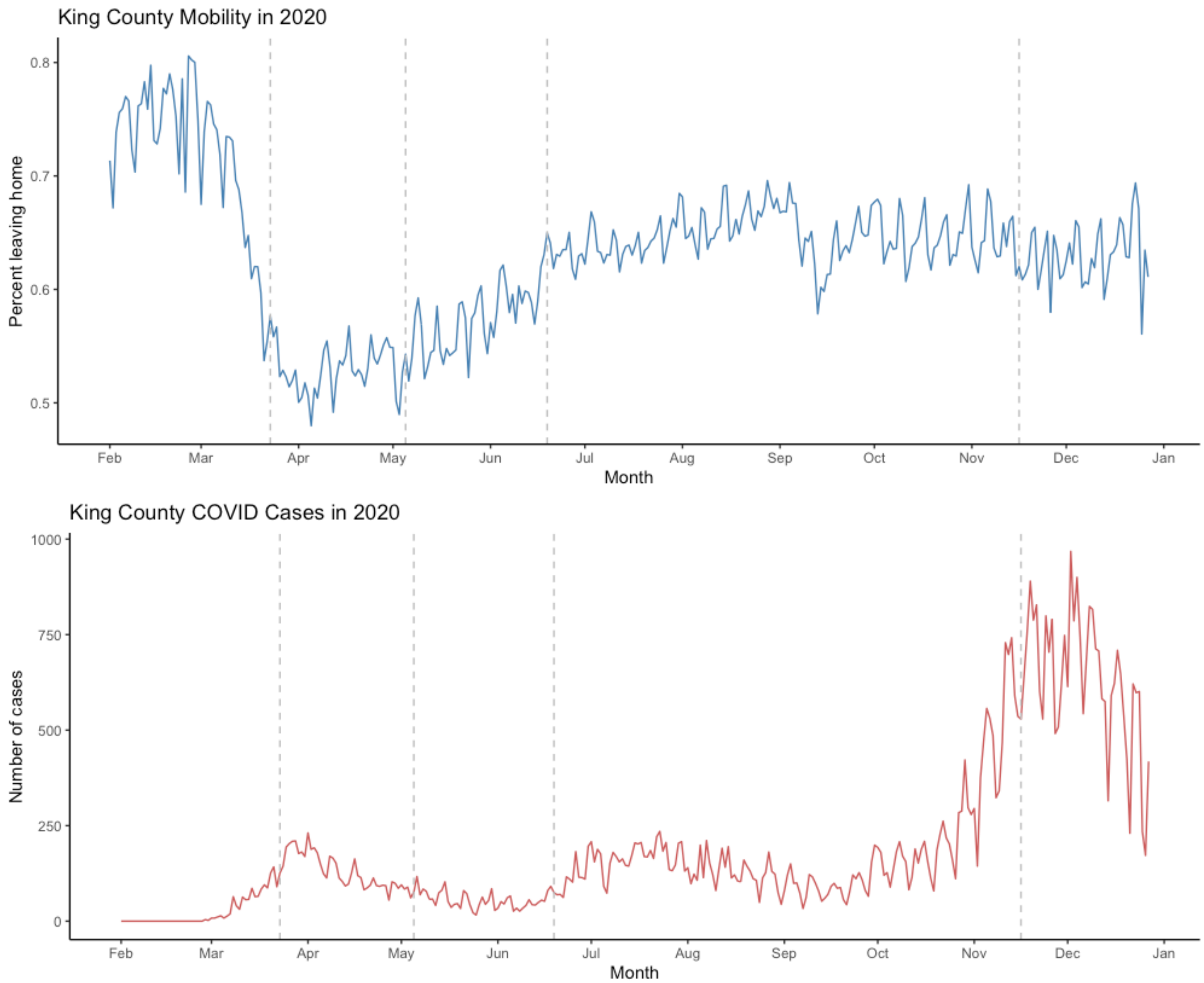

Figure 1. Changes in COVID-19 case counts and population mobility in King County during 2020. *Gray dotted lines indicate dates when changes in mitigation measures occurred.*

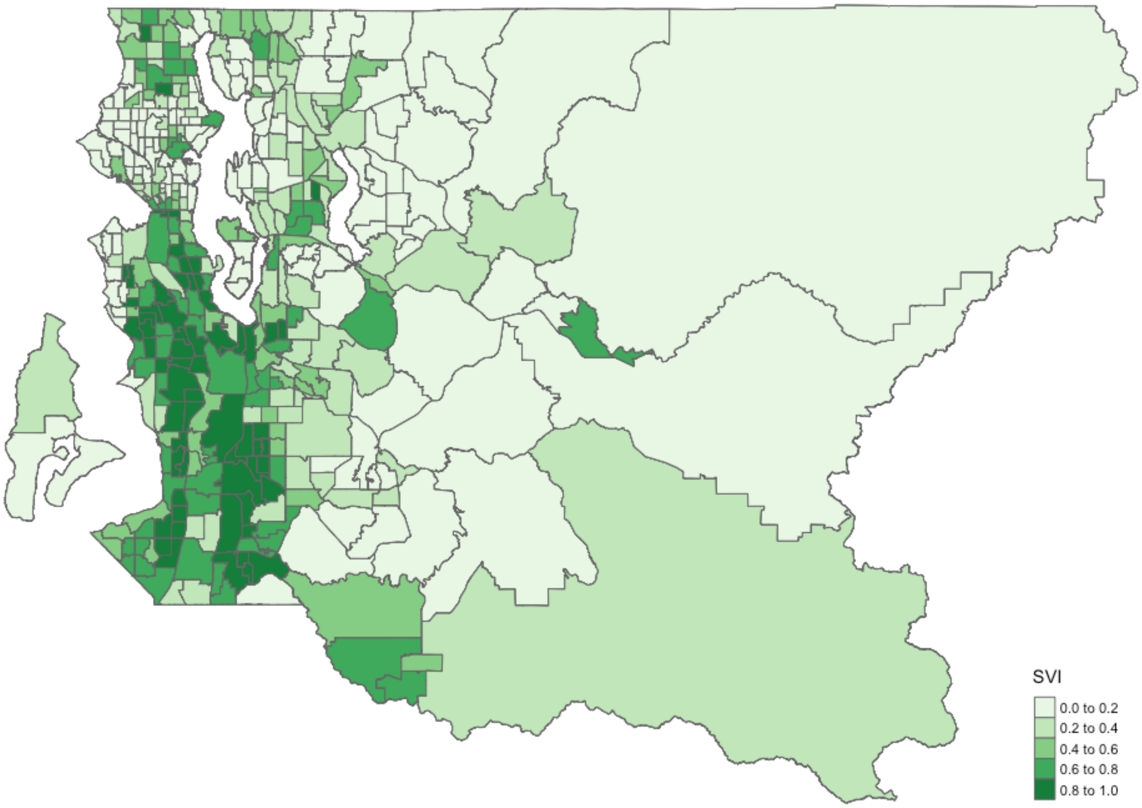

Figure 2. Social vulnerability index of census tracts in King County. *A ranking closer to 1 indicates less social vulnerability, while a ranking closer to 0 indicates more vulnerable tracts. SVI was calculated by the CDC as a percentile against all other tracts in Washington state using census data from 2018.*

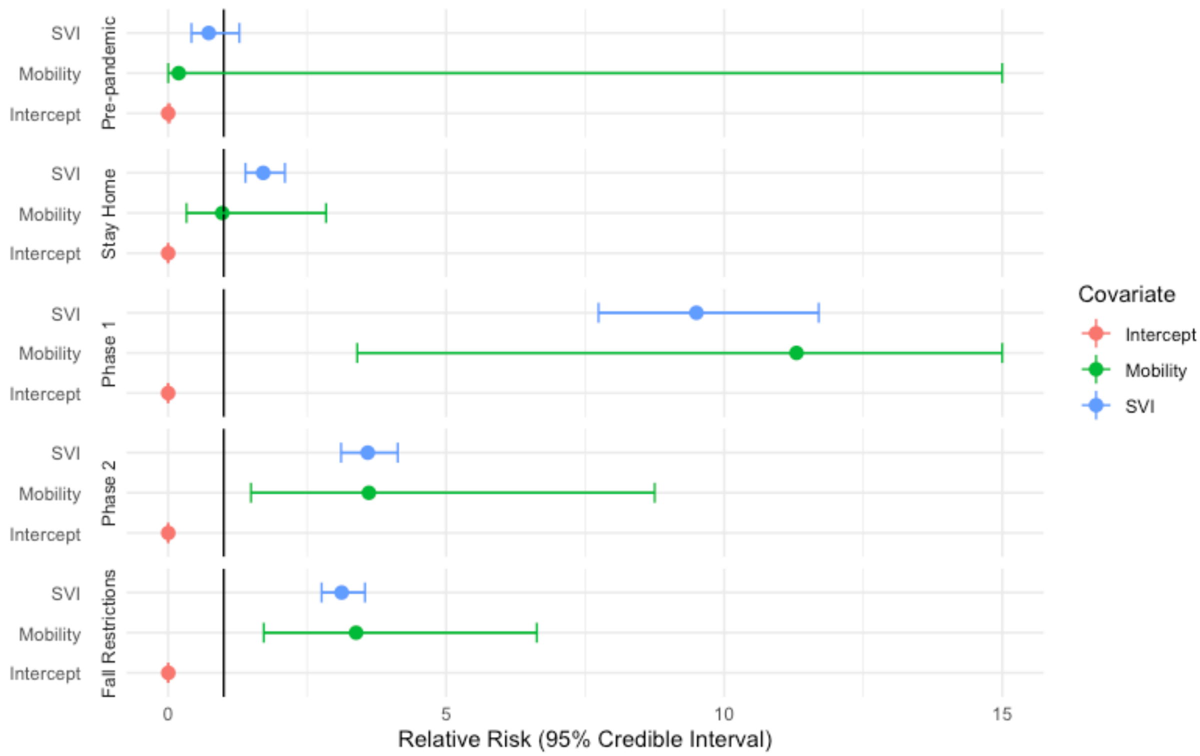

Figure 3. ***Relative risk of COVID-19 by model covariates****. Fixed effects from BYM Poisson-based models for each of the five time periods were exponentiated to obtain risk ratios. The x-axis was limited to 15 for interpretability. The upper limit of credible intervals for the mobility covariate in pre-pandemic and phase 1 periods were 21 and 38, respectively.*

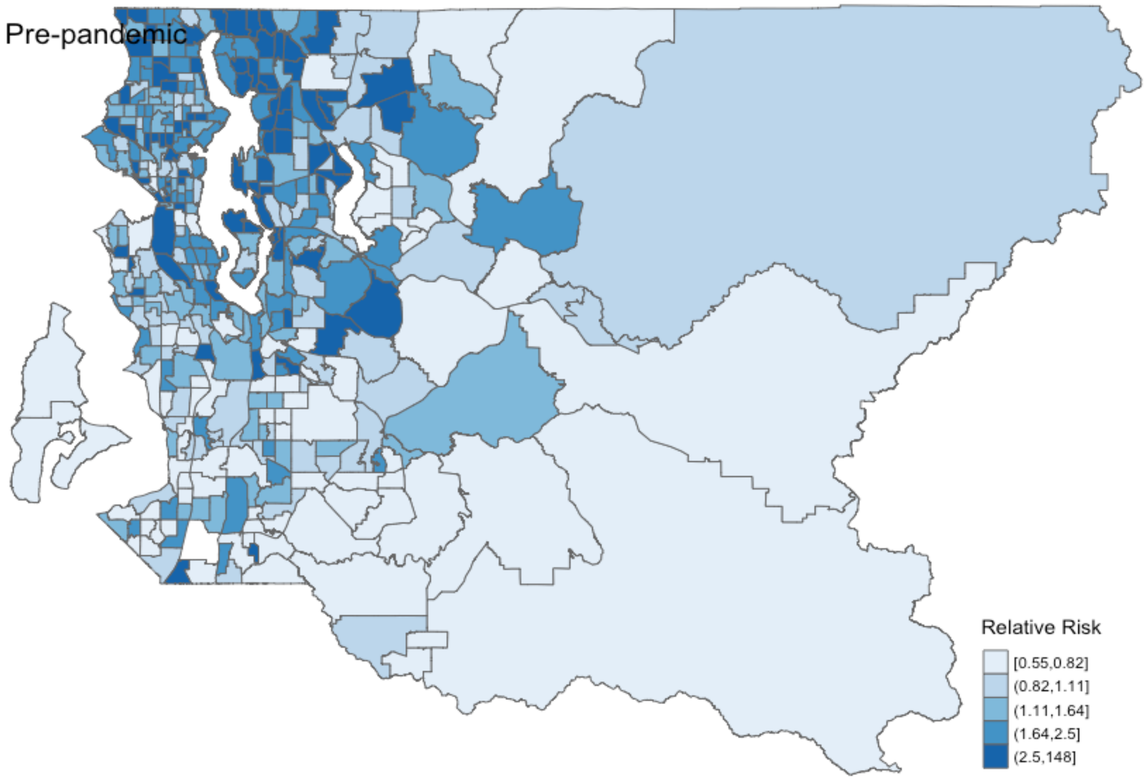

Figure 4A. Relative risks of COVID-19 case counts by mobility in King County prior to Stay Home, Stay Healthy.

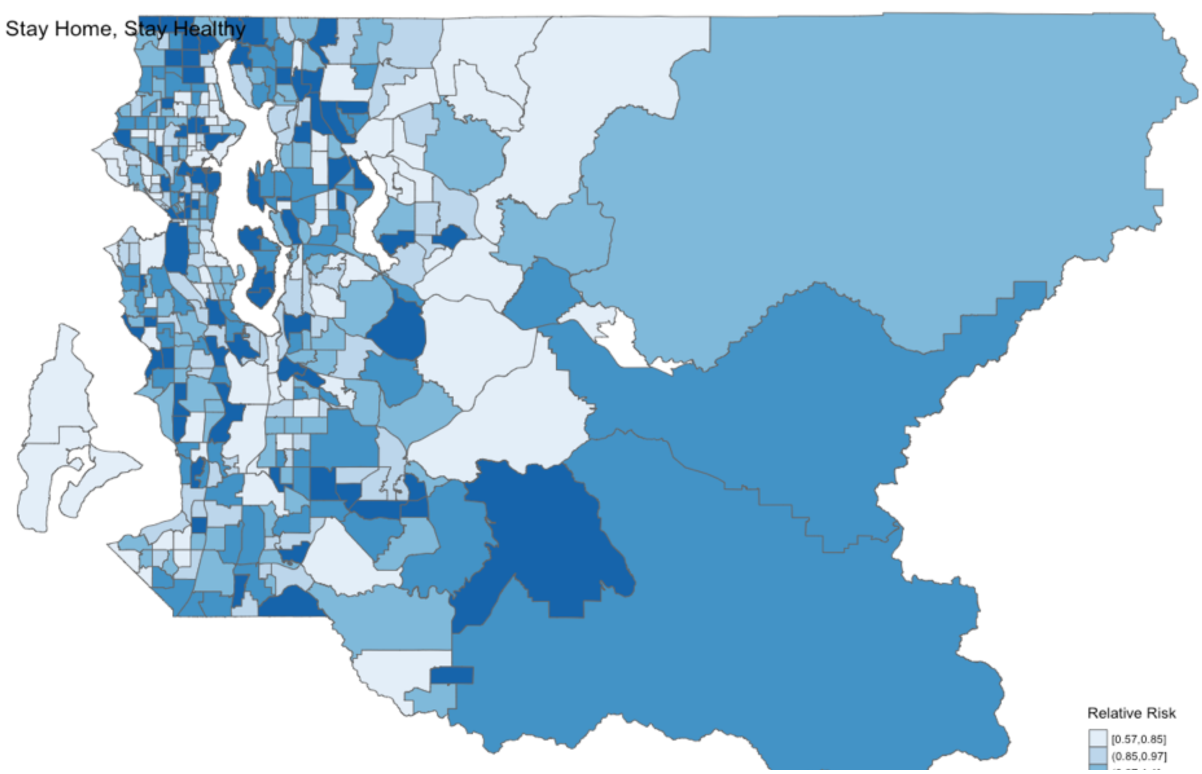

Figure 4B. Relative risks of COVID-19 case counts by mobility in King County during the statewide Stay Home, Stay Healthy order.

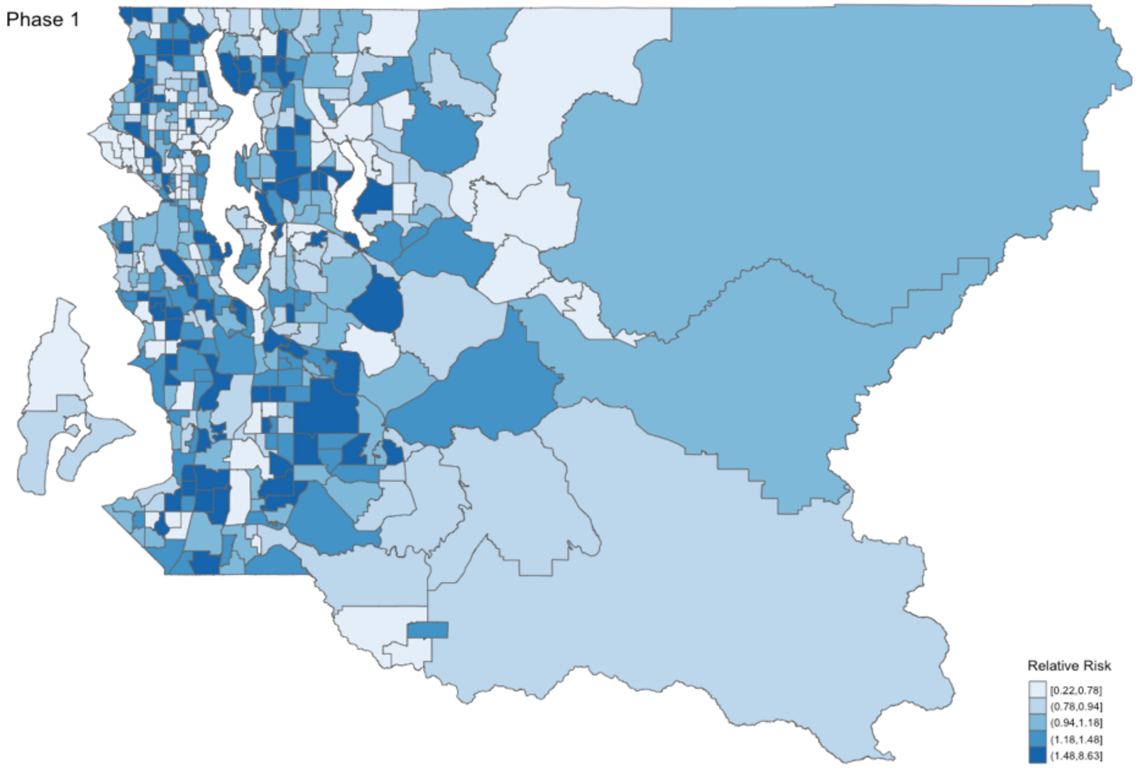

Figure 4C. Relative risks of COVID-19 case counts by mobility in King County during King County's Phase 1 reopening.

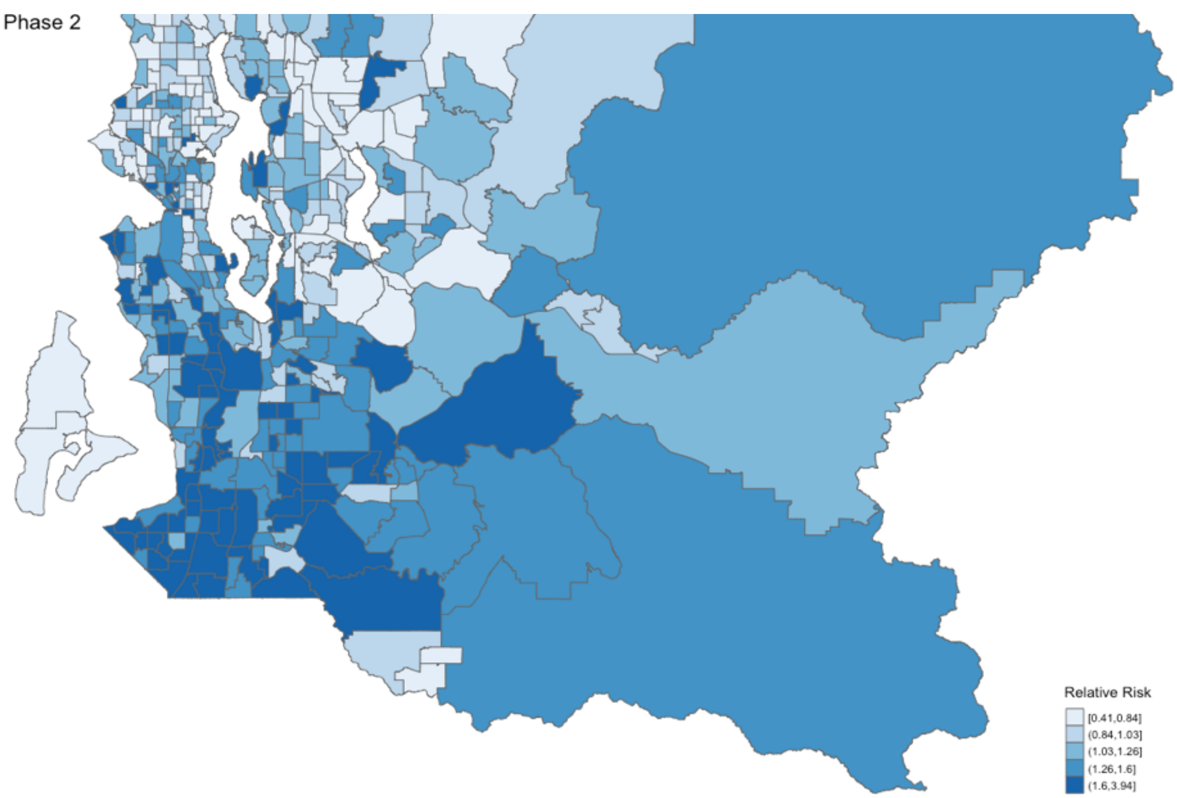

Figure 4D. Relative risk of COVID-19 case counts by mobility in King County during King County's Phase 2 reopening.

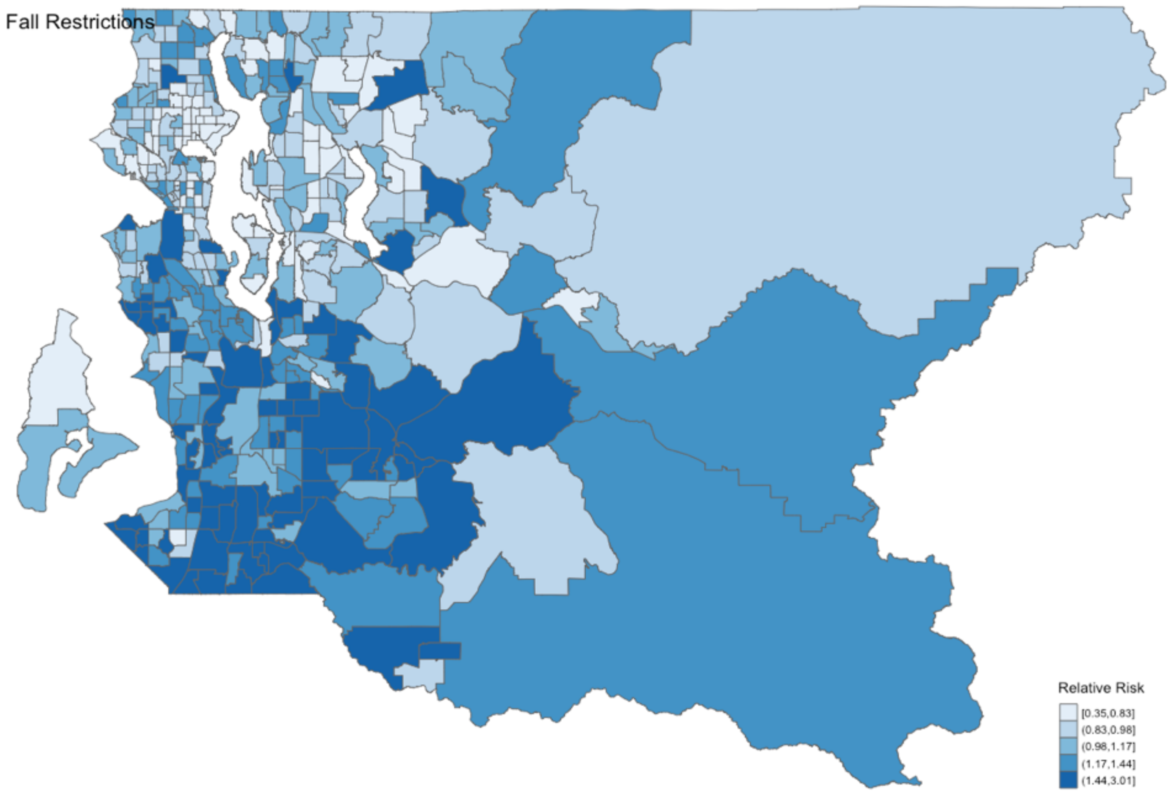

Figure 4E. Relative risks of COVID-19 case counts by mobility in King County during the statewide fall restriction period.