Stay-at-Home Orders, Mobility Patterns, and Spread of COVID-19

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Objectives. To understand how stay-at-home orders changed mobility patterns and influenced the spread of COVID-19.

Methods. I merged 2020 data from the Virginia Department of Health, Google Mobility Reports, and the US Census to estimate a series of 2-way fixed-effect event-study regression models.

Results. A stay-at-home order caused people to increase the amount of time spent at home by 12 percentage points and decrease the time the spent at work by 30 percentage points, retail and recreation venues by 40 percentage points, and grocery stores and pharmacies by 10 percentage points. People did not sustain changes in mobility and gradually returned to prepandemic levels before the stay-at-home order was lifted. In areas where people spent the most time at indoor locations, there was a large increase in COVID-19.

Conclusions. A more robust and stricter policy response coordinated at the national level combined with a strong economic response from policymakers could have increased the effectiveness of the stay-at-home order. (*Am J Public Health*. Published online ahead of print April 15, 2021:e1–e8. https://doi.org/10.2105/AJPH.2021.306209)

AJPH Published online ahead of print April 15, 2021

The United States did not have a uniform policy response to the COVID-19 pandemic, resulting in each state developing its own policy response. These policies largely consisted of nonpharmaceutical interventions (NPIs), or stay-at-home orders, limiting large gatherings, and promoting social distancing. These kinds of NPIs have been shown to be effective at reducing the spread of COVID-19.[1,2] Compliance with NPIs partially falls on individual businesses to enforce the specific mandates from the state, and it partially falls on individual people to comply and alter their behavior. If both business and people do not fully comply, the effectiveness of the NPI decreases.

The NPIs implemented by Virginia are similar to those of many states. On March 12, 2020, the governor of Virginia declared a state of emergency and, on March 25, 2020, issued a stay-at-home order that closed all nonessential businesses, limited gatherings to 10 people, and closed all public schools for the remainder of the academic year. The stay-at-home order would remain in effect until May 15, 2020, when Virginia began a 3-phase reopening. What makes Virginia unique is that the spread of COVID-19 was not uniform across the state. When splitting up Virginia into its 3 major metropolitan statistical areas (MSAs)—Hampton Roads, Richmond, and Northern Virginia (shown in Figure 1)—Northern Virginia and Richmond saw an increase in new cases at the start of the pandemic peaking in early June, whereas Hampton Roads did not start to see a significant increase in cases until late June and peaked in late August, which can be seen in Figure 2. It is possible that some of these differences could be attributable to differences in testing. Hampton Roads and Northern Virginia administered about the same number of tests per capita, and Richmond administered more tests per capita throughout the study period. However, all 3 MSAs saw testing increase at the same growth rate with parallel trends, so testing likely did not contribute to the changing dynamics over the study period or between the MSAs. These differing trends make Virginia a good candidate to study how people's mobility patterns may have influenced the spread of COVID-19 differently across the MSAs. In addition, data from the US Census[3] in Table A (available as a supplement to the online version of this article at http://www.ajph.org) show that

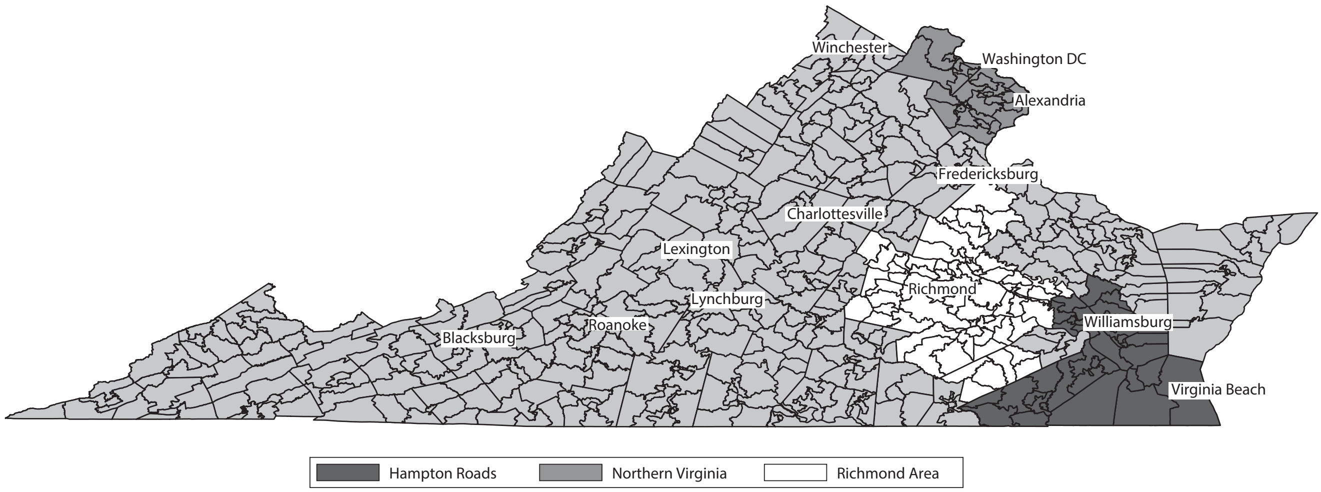

FIGURE 1— Map of Virginia With Major Metropolitan Statistical Areas

Source. Author's calculations using shapefile data from the US Census Bureau.

AJPH Published online ahead of print April 15, 2021

Virginia is relatively representative of the United States.

While ultimately mass testing, contact tracing, and the development of a vaccine are the best ways to combat a pandemic, these can take time to develop and produce. In the event of a future pandemic, immediate government response can have large downstream effects on public health and mitigation.[4] The United States was slow to respond to the COVID-19 pandemic. Rice[5] notes that even waiting a week to implement policies can have large consequences in the number of cases and death. This article provides some insights into the effectiveness of the policies implemented in Virginia and how people's behavior changed in response in hopes that in a future pandemic these results might be useful to public health officials and policymakers to make quicker and more informed decisions to help slow the spread of disease.

METHODS

The data used in this study came from multiple sources and covered the period of February 15 through August 28, 2020. Since the start of the pandemic, Google has made cellphone location data publicly available to study COVID-19. The Google Community Mobility Reports[6] provide de-identified data aggregated up to the county level that track mobility patterns for smartphone users who have Google location history turned on (see Aktay et al.[7] for more information on this process). Average daily mobility patterns for each county are reported as a percent change from a baseline period before the start of the pandemic between January 3 and February 6, 2020. Data on COVID-19 cases came from the Virginia Department of Health.[8] County population estimates for 2020 in Virginia came from the University of Virginia Weldon Cooper Center for Public Service.[9] Location and shapefile data were used to generate the map in Figure 1, and population density came from the US Census Bureau.[10] Weather data came from the National Oceanic and Atmospheric Administration.[11]

To study the impact of Virginia's stay-at-home order and phased reopening on COVID-19 cases and mobility patterns, I estimated a series of 2-way fixed-effect event-study specifications in which the regressions took the following form:

$$(1)\qquad Y_{i,t} = \beta_0 + \sum_{j \neq 3/25} \beta_j D_{i,t} + \gamma R_{i,t-1} + \theta X_{i,t} + d_t + \varphi_i + \varepsilon_{i,t}$$

where $D_{i,t}$ is a set of daily event time dummy variables that take a 1 on a particular day, t, at location i and 0 for all other days not t. I omitted the dummy variable for February 20, 2020. Thus, the coefficients for β_j measure the impact of the stay-at-home order at time j relative to 35 days before it was implemented on March 25, 2020. I included binned dummy variables for the first and last 5 days of the sample, but did not report them. The interpretation of these event time dummy variables is the change relative to February 20, 2020. The event time dummy variables are presented graphically with 95% confidence intervals clustered at the county level.

$R_{i,t-1}$ is the inverse hyperbolic sine (IHS) of total cases in location i at time $t-1$. The IHS has similar properties to the log transformation but allows for zero-value observations, which is necessary when counting COVID-19 cases near the beginning of the pandemic for

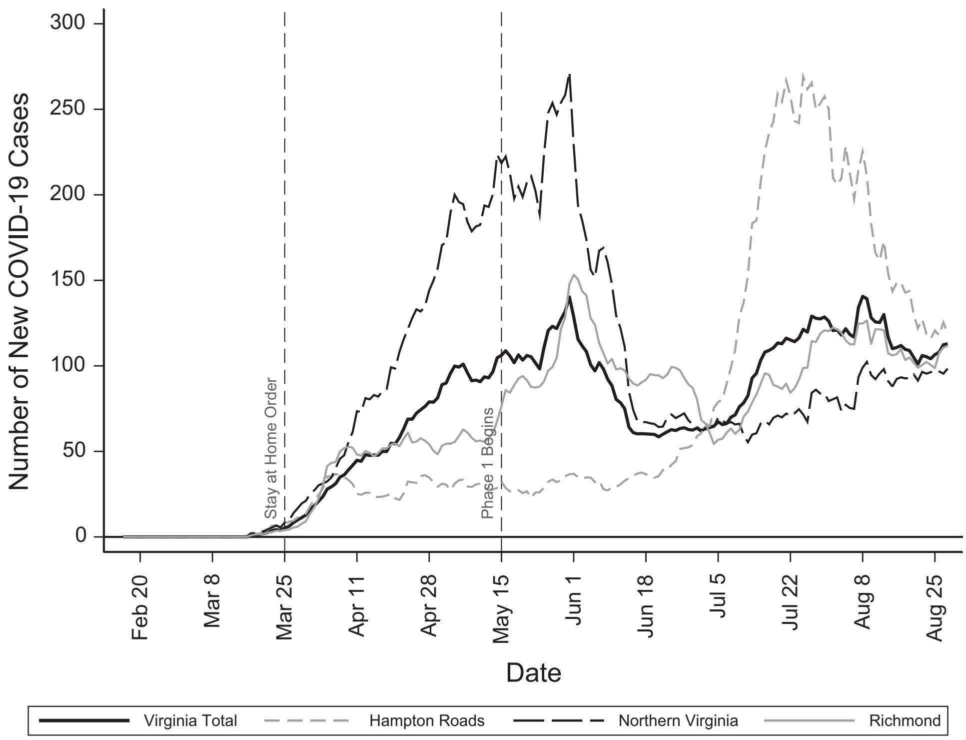

FIGURE 2— Daily New Cases of COVID-19 per 1000 People in Virginia

Source. Author's calculations using data from the Virginia Department of Health.
Note. Graph shows a 7-d moving average of COVID-19 cases in Virginia per 1000 people.

some counties.[12–14] $X_{i,t}$ is a set of county-specific variables controlling for differences in weather that include a dummy variable for if it rains, a dummy variable for hot days when the temperature is above 32.2°C (90°F), and a dummy variable for cold days when the temperature is below 0°C (32°F). d_t denotes a month fixed effect and φ_i denotes a county fixed effect. The fixed effects are of particular importance to this specification because of the short time period of this study. They will capture differences in population density and urban status as those will not change during the study period and daily media announcements that may affect individual mobility patterns. The majority of people get their news from the same sources,[15] and, because the coverage of the pandemic likely did not change much during the study period, media coverage is likely covered in the fixed effects, although imperfectly. The fixed effects will also likely capture other unmeasured omitted variables because of the short period covered in this study, though it cannot be said with certainty that there is not some omitted-variable bias.

This study presents a series of event-studies with different independent variables ($Y_{i,t}$). First, a set of event-studies is presented separately for the 7-day moving average of the mobility patterns in the following venues: for time spent at home, a location of work, at retail and recreation venues (including restaurants and bars), and grocery stores and pharmacies. Second, a separate event-study was conducted in which the IHS of daily COVID-19 cases per 1000 people was the variable of interest ($Y_{i,t}$).

For the regression in which the IHS of daily COVID-19 cases per 1000 people is the variable of interest, the interpretation of the regression coefficients for β_j can be interpreted as semielasticities (or percent change) by applying the transformation of $\exp(b_j) - 1$ as proposed by Bellemare and Wichman.[16] Results report both the IHS coefficients and the semielasticities. All regressions were estimated separately for the entire state of Virginia and the 3 major metropolitan areas of Hampton Roads, Richmond, and Northern Virginia. I conducted all data analyses using the statistical software Stata version 16.1 (StataCorp LLC, College Station, TX).

RESULTS

In this section, I discuss the results from how the stay-at-home order in Virginia affected both mobility patterns and new

AJPH Published online ahead of print April 15, 2021

cases of COVID-19 using the event-study methodology laid out in the Methods section.

Mobility Patterns

Figure A (available as a supplement to the online version of this article at http://www.ajph.org) shows the results graphically of the event-study regressions for all of Virginia (the full regression output for all regressions can be found in Tables B through F, available as supplements to the online version of this article at http://www.ajph.org). Figure A, Panel A, shows that, following the stay-at-home order, people decreased the amount of time they spent at their place of work by more than 30 percentage points. People started to spend less time at work several weeks before the stay-at-home order was declared, likely an anticipation effect as the governor of Virginia declared a state of emergency on March 12, 2020. After around April 15, 2020, people started to increase the amount of time at their place of work. After Virginia began its phased reopening on May 15, 2020, people have been spending around 15 percentage points less time at their place of work. Correspondingly, Figure A, Panel B, shows the opposite trend for time spent at home. After the stay-at-home order was declared, people were spending around 12 percentage points more time at home than they were before the pandemic; however, this was short-lived as there was a gradual trend downward that started immediately. By mid-June, people were spending the same amount of time at home as they were before the start of the pandemic.

Figure A, Panel C, shows that people had a significant decrease of more than 40 percentage points at retail and recreation venues, which include restaurants and bars, just after the stay-at-home order was issued. However, almost immediately, people started to gradually increase the amount of time they spent at these primarily indoor locations and returned to their pre-pandemic level by early June.

Figure A, Panel D, shows that there was a large increase in the amount of time spent at grocery stores in the weeks just before the stay-at-home order was declared, which was followed by a decrease to around of 10 percentage points less time relative to before the pandemic. This pattern is likely in response to the demand-shock that typically occurs at the beginning of a pandemic or natural disaster as people were preparing for the possibility of being stuck at home for an extended period of time and the possibility of a future supply shock to goods they need.[17,18]

Figure 3 shows the results graphically of the event-study regressions separated by MSA. All 3 MSAs generally show the same trend as the entire state, but with different magnitudes. People living in Northern Virginia had a greater response to the stay-at-home order compared with people in Hampton Roads and Richmond. They spent a greater amount of time at home, and significantly less time at their place of work, at retail and recreation venues, and at grocery stores and pharmacies.

People in Hampton Roads and Richmond did not change their mobility patterns to the extent of people in Northern Virginia. The most notable difference in mobility patterns was for time spent at retail and recreation venues, which are primarily indoor locations that include restaurants, bars, and shopping centers. Figure 3, Panel C, shows that people in Richmond were spending the same amount of time at these locations as before the start of the pandemic, but people in Hampton Roads were spending more time at these locations than before the start of the pandemic.

New COVID-19 Cases

Figure B shows the results of the event-study regressions for new daily COVID-19 cases in Virginia in total separated by MSA, and Figure C shows the transformation of those results to semielasticities. The regression results conceptually show the same pattern as Figure 2, while introducing controls for cross-county differences and local concentration of COVID-19 cases, but with large 95% confidence intervals. All of the figures show that Northern Virginia and Richmond had an increase in cases between March and late May, whereas Hampton Roads saw a relatively flat number of cases until mid-June when there was a large increase peaking in late August. It is important to also understand how new COVID-19 cases and changes in mobility are related.

It is important to also understand how new COVID-19 cases and changes in mobility are related. Figure 4 shows the correlation between changes in mobility patterns and the percent change in daily COVID-19 cases 11 days later in a similar fashion to Li et al.[19] Figure 4 shows that there is a negative correlation in more than 60% of the counties in Virginia between time spent at home and COVID-19 cases 11 days later, indicating that an increase in time spent at home led to a decrease in new COVID-19 cases. Figure 4 also shows that there is a positive correlation in more than 60% of the counties in Virginia for time spent at work, retail and recreation, and grocery and pharmacy, indicating that an

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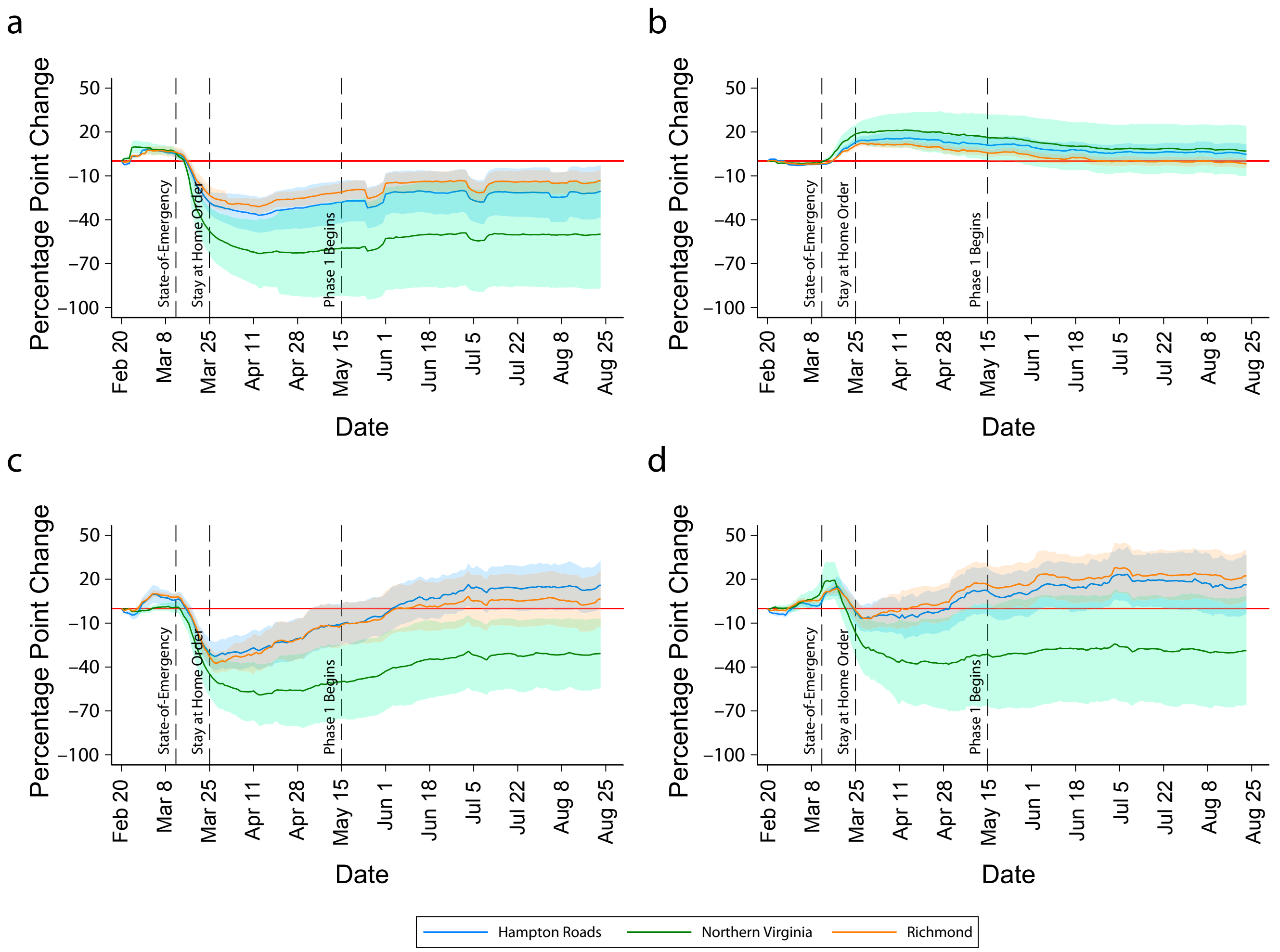

FIGURE 3— Two-Way Fixed Effect Event-Study Results for Mobility Patterns in Virginia by Metropolitan Statistical Area for (a) Places of Work, (b) Home, (c) Retail and Recreation, and (d) Grocery and Pharmacy: February 2020–August 2020

Note. Each line in each graph represents the results of a separate 2-way fixed-effect event-study regression of the specified mobility pattern. The solid line represents the point estimates of $D_{i,t}$ from equation 1. The base date of comparison is February 20, 2020. Controls included in the regressions are the lagged inverse hyperbolic sine of total cases, population density, urban status, a month fixed effect, and a county fixed effect. The shaded area represents a 95% confidence interval of the point estimate clustered at the county level.

increase in time spent at these locations led to an increase in new COVID-19 cases.

DISCUSSION

The COVID-19 pandemic forced many people make changes to their daily lives—working from home, not going to the gym, not going out to eat—to slow the spread of COVID-19. Many of these changes were in response to NPIs (or stay-at-home orders) implemented by state and local governments. For the NPIs to work, this requires enforcement by businesses and cooperation by individuals. It is important to understand how people responded to the stay-at-home order to gauge the effectiveness of these measures in combating the spread of COVID-19. Virginia presents a unique opportunity to do so by comparing how people changed their mobility patterns as there was not a uniform pattern in COVID-19 cases across the state. There are 2 noteworthy trends in mobility patterns. First, people initially responded to the stay-at-home order with a large change in mobility patterns, but, almost immediately, they gradually began to trend back to prepandemic levels. Second, people in Hampton Roads started spending a greater amount of time at indoor locations compared with the other MSAs and prepandemic levels while at the same time seeing an increase in COVID-19 cases.

Declaring a stay-at-home order was successful at getting people to increase

AJPH Published online ahead of print April 15, 2021

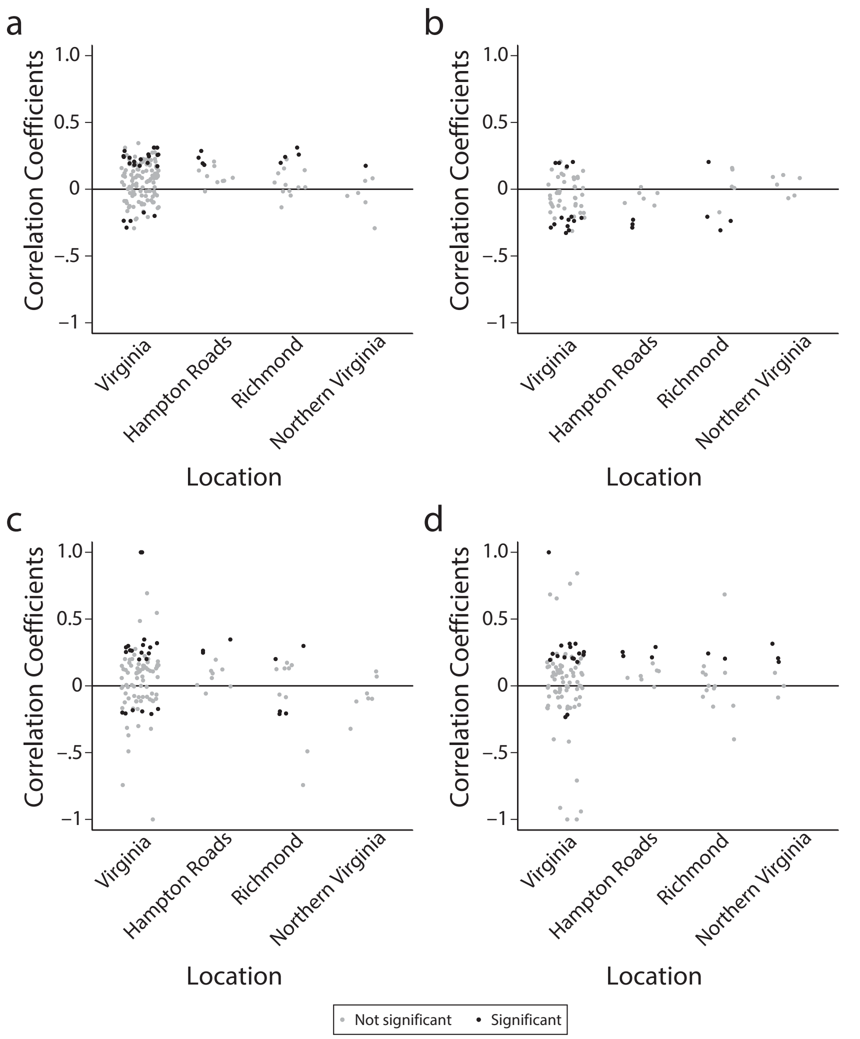

FIGURE 4— Correlation Between Changes in Mobility and Change in COVID-19 Cases in Virginia for (a) Places of Work, (b) Home, (c) Retail and Recreation, and (d) Grocery and Pharmacy: February 2020–August 2020

Source. Author's calculations using Google Mobility Reports and data from the Virginia Department of Health.
Note. Each panel shows the correlation between changes in mobility patterns for that venue and percentage change in new COVID-19 cases 11 d later. Significance is $P < .05$.

the amount of time they spent at home and decrease the amount of time they spent at work and other indoor locations such as retail and recreation venues, grocery stores, and pharmacies. Given the correlations seen in Figure 4, these changes in mobility patterns likely led to decreases in new cases of COVID-19 cases. People mostly stayed away from their location of work, as they were shut down by the NPI. However, almost immediately, people started to decrease the amount of time they were spending at home and increase the amount of time they spent at retail and recreation venues. There are several likely causes of this. During a pandemic, people faced a trade-off between income and health[20] and being under a stay-at-home order increases anxiety about health, worrying about financial security, and loneliness.[21] While the United States provided a relief package that issued a one-time $1200 stimulus check and increased unemployment benefits by $600 per week, those benefits expired at the end of July. Political deadlock prevented further stimulus. With only 25% of the US population able to work from home,[22] some people needed to return to work who otherwise would have stayed at home had there been a stronger relief and stimulus package. In addition, the NPIs issued by individual states in response to COVID-19 became politicized and criticized by President Trump and some Republican members of Congress.[23] This could have created uncertainty as to the effectiveness and need for NPIs causing some people to resume normal activities.

As seen in Figure 1, Northern Virginia experienced a much higher volume of COVID-19 cases at the beginning of the pandemic. This may have caused people living there to be more vigilant, which led to the larger change in mobility patterns compared with the other MSAs. This, in turn, may have led to the lower volume of COVID-19 cases in Northern Virginia after the state began its phased reopening.

After Northern Virginia and Richmond saw a large decrease in daily COVID-19 cases, Hampton Roads saw a large increase in cases. In the weeks leading up to this increase in cases, people in Hampton Roads increased the amount of time they spent at primarily indoor locations—such as restaurants, bars, shopping centers, and recreation venues—that Figure 4 shows are correlated with increases in new COVID-19 cases. People in Hampton Roads were spending more time at these locations starting in early June than they were before the start of the pandemic, and

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people from Richmond and Northern Virginia were either at or below prepandemic levels. This increase in time spent at primarily indoor locations could be the reason for the increase and the high volume of COVID-19 cases in Hampton Roads in July and August that corresponds with an increase in time spent at retail and recreation venues. Spending a prolonged period of time at indoor locations increases the risk of COVID-19 transmission.[24,25] This risk is 18.7% higher compared with outdoor locations.[26] It is likely that the amount of time people in Hampton Roads were spending at retail and recreation venues relative to prepandemic levels after the phased reopening began was a large factor in the high number of COVID-19 cases in that MSA.

As this study was not able to draw a causal estimate between mobility and COVID-19 cases, it is important to note that there are other possible causes of the increased rates of COVID-19 cases in Hampton Roads in July and August—most notably, tourism. Hampton Roads is a tourist destination, primarily in Virginia Beach. Smith Travel Research[27] reports that, in late August, hotel occupancy was less than 50% nationwide; however, the only major market to have hotel occupancy above 60% was Virginia Beach and Norfolk, Virginia, indicating an increase in tourist travel to the region. However, the Virginia Department of Health does not believe tourism is responsible for the increase in COVID-19 cases in Hampton Roads.[28]

Limitations

There are several limitations to this study. First, the Google Community Mobility Reports only show data for users who have opted into location tracking. It is possible that there are differences in users who opt-in versus those who do not and that they do not display the same mobility changes. Second, data used in this study were aggregated by county and not individual-level data, and, therefore, the trends cannot be analyzed by demographics and other characteristics. Third, as noted in Liu,[29] there are possibly unobserved factors yet to be measured and fully understood that could potentially affect people's behavior in response to the NPIs attributable to how recent the study period is. Last, the results of this study can likely be extended to the United States as a whole and to individual states with similar social, economic, and political environments. However, it is possible that states that differ significantly socially, economically, and politically may have experienced different patterns and the results of this study may not be generalized to them.

Public Health Implications

Understanding the degree to which NPIs, such as stay-at-home orders, were effective in getting people to alter their behavior to stop the spread of COVID-19 will be valuable to public health officials and policymakers in the event of a future pandemic. Not only will a fast and strict public policy response mitigate the spread of disease, but it also can lead to a faster economic recovery.[30–32] This study helps identify how people changed their mobility patterns because of a stay-at-home order. I show that an NPI, such as the stay-at-home order declared in Virginia, was successful in getting people to spend more time at home, less time at their place of work, and less time at other indoor locations. However, people did not exhibit a sustained change in their mobility patterns, likely attributable to a combination of inconsistent messaging from policymakers, income-related issues, and social needs. I also show that in areas where people had the largest increase in time spent at primarily indoor locations after the beginning of a phased reopening, there was a corresponding increase in new COVID-19 cases.

Public health officials and policymakers can learn from these patterns to improve NPIs in the event of a future pandemic. A clear and consistent public relations campaign coordinated nationally will likely have a stronger and more effective response to NPI measures. Furthermore, ensuring that people do not have to weigh the tradeoff between income and health can make it easier for people to comply with a stay-at-home order. Policymakers should consider more robust stimuli to ensure that people are able to maintain their income during a pandemic if they are unable to work from home. Lastly, public health officials and policymakers should consider additional or stricter NPIs to see a sustained change in mobility patterns. When beginning a phased reopening, stricter rules on indoor activities may be warranted as this study shows that an increased time spent at these locations may be a strong contributing factor to an increase in the spread of disease. Stronger and stricter NPIs that are coordinated at the national level may help slow the spread of a future pandemic, which, in turn, would improve the welfare of many people in the country. Future studies should seek to continue to learn more about how individual people responded and specific different demographic groups responded to NPIs to help inform public health officials and policymakers of additional ways public policy can help

AJPH Published online ahead of print April 15, 2021

stop the spread of disease during a pandemic. AJPH

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PUBLICATION INFORMATION

Full Citation: Murray T. Stay-at-home orders, mobility patterns, and spread of COVID-19. *Am J Public Health*. Published online ahead of print April 15, 2021:e1–e8.

Acceptance Date: January 19, 2021.

DOI: https://doi.org/10.2105/AJPH.2021.306209

ACKNOWLEDGMENTS

The author gratefully thanks Joseph Lucibello for his assistance collecting data on the weather and Gabrielle E.W. Giersch, PhD, for her helpful thoughts and comments.

CONFLICTS OF INTEREST

The author has no conflicts of interest to declare.

HUMAN PARTICIPANT PROTECTION

No human participant protection was required for this study as all data analysis was conducted using de-identified data that were collected by third parties.

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AJPH Published online ahead of print April 15, 2021