The Influence of Broadband on People's Mobility During Early Stages of COVID-19

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We examine people's tendencies to stay at home and go to traditional places of work during the early stages of the pandemic in the United States. We found no statistically significant impact of home broadband on people's tendency to stay at home. We did find home broadband to have a small, but statistically significant negative impact on people's tendency to go to their traditional workplaces. Age demographics, household income, college education, proportion of blue-collar jobs, and metropolitan status were more important factors in explaining people's tendencies to stay in lockdown.

Keywords: COVID-19, Mobility, Broadband, Unemployment

JEL codes: I18, K32, L86

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1 Introduction

Information and communications technologies (ICT) played important roles in people's responses to COVID-19. The virus emerged in China in late 2019 and soon made its way across the world. Within four months one-third of the world's population, eventually including over 90% of Americans, was in lockdown. Government officials ordered lockdowns based in part on the belief that restricting human mobility would limit the spread of the virus. But lockdowns come at a cost and affect different people differently, in part because of differences in people's abilities to use ICT. For example, many white-collar workers can work from home using broadband, but that is not true for blue collar workers performing physical labor. When schools and universities switched from traditional instruction to distance learning, students in households with broadband connections found it easier to engage in schoolwork than did those in non-connected households.

These differences in impact imply that people's use of ICT might affect their responses to the lockdown orders. We examine this issue. More specifically, we study how the presence of broadband in people's homes in the United States affected their propensities to follow the spirit, if not the letter, of lockdown orders by staying home more and by going to work less during the early weeks of the lockdowns, namely the last two weeks of March and all five weeks of April 2020. We find that the presence of broadband had little measurable impact on people's tendencies to stay home during these weeks. It had a greater and more consistent impact on whether people tended to go to work: Having broadband in their homes made people less likely to go to work. So, home broadband did not necessarily prompt people to stay home, but it did limit their going to their traditional workplaces. To understand this workplace effect better, we also examine to what extent home broadband affected unemployment. The ability to work remotely using home broadband should make it more likely that people would keep their jobs. But we found otherwise: we found unemployment rates increased more in areas with higher home broadband penetration. So, it appears that in the early stages of the lockdowns, home broadband did not facilitate social distancing with respect to people staying home. But home broadband did make it less likely for people to congregate at workplaces, although sometimes because people had lost their jobs.

We reach these conclusions by examining county-level factors that influence people's tendencies to stay home or go to work during the second half of March and the entirety of April, using

Google's Mobility Data and the US Census Bureau's American Community Survey (ACS) statistics. In addition to examining the influence of home broadband, we study the impacts of news about the spread of the virus, the timing of lockdowns, income, proportion of jobs that are blue collar, and other factors. We find that the effect of broadband is small relative to these other factors, even when broadband is statistically significant. For example, we find that both a greater proportion of college educated residents and a higher proportion of households having broadband made it less likely that people went to their traditional workplaces. But the effect of a one percentage point difference in college educated households was approximately five times that of a one percentage point difference in home broadband penetration.

We use three models to obtain our results. Our first model examines the difference in the amount of time that people spent at home relative to a baseline period of January 3 through February 6, 2020, and our second model examines the difference in people's number of visits to their traditional workplaces, relative to the same baseline period. We estimate results for each of the last two weeks of March and all five weeks of April, controlling for when a state ordered its lockdown. To further study the effect of a state's lockdown, we also estimate results for each of the two weeks before a state-ordered lockdown and for each of the four weeks following the lockdown order. Our third model studies unemployment using monthly data by county. We compare unemployment rates for March and April to the rates in January.

Regarding people's propensities to stay at home, we find that broadband had no statistically significant effect when we include state dummy variables. People did stay home more if there were more reported cases of COVID-19, people had higher incomes, or there were lower proportions of blue-collar workers, more college educated residents, more residents of Asian descent, or younger residents. Population density had a positive impact on people's tendencies to stay home, as did having a Republican governor or having a state-ordered lockdown.

Our results for people's tendencies to visit their traditional workplaces complement our stay-at-home results, but with some minor differences, implying that people also altered their habits for going to other places, such as grocery stores. Home broadband made people less likely to go to workplaces, as did more reported cases of COVID-19, higher incomes, more college educated persons, more people of Asian descent, and more people of working age. Blue collar workers were more likely to go to their workplaces, as were Blacks who were more likely to go to their workplaces than other racial groups. People in states with a Republican governor were more like to go to work, while a state lockdown makes people less likely.

Our unemployment model helps explain the changes in workplace mobility. We find greater increases in unemployment rates being positively correlated with home broadband, more COVID-19 cases, more blue-collar, greater population density, and having a Democratic governor. Some impacts are different between March and April: Having more COVID-19 cases is statistically significant in April, but not in March. Blue collar workers were more likely to keep their jobs in March but bore the brunt of job losses in April.

The rest of this paper is organized as follows. Section 2 provides background and a literature review. Section 3 describes our modeling approach and data. Section 4 is our results. The last section is our conclusion.

2 Background and Literature

The number of COVID-19 cases spread rapidly in the United States in the latter part of February. The hardest hit places initially were major hub cities along the east and west coasts, such as cities in Washington, New York, and California. As the number of cases rose in late March, the Center for Disease Control (CDC) began recommending social distancing measures to combat the spread of the virus and many states started lockdown procedures.

Figure 1 shows the pace at which US citizens came under lockdown orders. Lockdowns began on March 19 when over 37 million people came under lockdown directives. By the end of March, the number had increased to 203 million, or two-thirds of the country's population, excluding Alaska, Puerto Rico, and minor islands[1]. The lockdowns peaked on April 7, when 95% of the population came under lockdown orders.

[Place Figure 1 about here]

[1] Data obtained from New York Times Coronavirus tracker. Alaska excluded in the and later analysis due to mobility data unavailability. https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

Figure 2 shows numbers of states coming under lockdown orders, separated by the political parties of the state governors, for the 49 continental states and the District of Columbia. Governorships (or mayorship for the District of Columbia) are evenly divided between Democrat and Republican governors: There are 25 Republican governors and 24 Democrat governors, plus the mayor of the District of Columbia is a Democrat. As the figure shows, states with Democratic governors (shown by the blue line) began locking down first and the number of states with Republican governors (shown by the red line) never equaled the Democrat number. The first Republican state to order a lockdown came three days after the first Democrat state. The number of Republican states with lockdown stayed far below the number of Democrat states until April 1, when all Democrat-led states came under lockdown. The number of Republican-led states under lockdown continued to grow, but five states never had lockdown directives: Arkansas, Iowa, Nebraska, North Dakota, and Wyoming.

[Place Figure 2 about here]

As lockdowns spread, people's mobility fell. Figure 3 shows how the amount of time that people spent at home and how their number of visits to their traditional workplaces changed from the baseline period through March and April. The vertical axes show changes in the time spent at home or visits to work and the horizontal axes are calendar weeks. Even though lockdowns did not begin until March 19, we can see behavioral changes beginning the second week of March when there was a small percentage increase in people's time at home and a small decrease in people going to their workplaces. This changed significantly in the third and fourth weeks of March, corresponding to the rapid growth in lockdowns shown in Figures 1 and 2. Through the first two weeks of April, the numbers of people staying home continued to grow and the numbers of people going to workplaces continued to shrink. These trends began reversing the third week of April.

[Place Figure 3 about here]

Figure 4 shows people's changes in time spent and home and visits to workplaces relative to the dates they came under lockdown orders. The vertical axes show the change in mobility and the horizontal axes show the number of weeks before and after lockdown. On the horizontal axes, "-X" means X weeks prior to the lockdown and "X" means the number of weeks of the lockdown, with X=1 being the first week of lockdown. Figure 4 shows that people began social distancing behaviors before receiving lockdown orders. Three weeks prior to the beginning of lockdowns, people began increasing their staying at home and began decreasing their going to work. Their tendencies to stay home and to not go to work stabilized once lockdown orders were given.

[Place Figure 4 about here]

Scholars began studying patterns of lockdown under COVID-19 almost as soon as the lockdowns began. Brodeur et al. (2020) provide an early and useful literature survey. The number of studies is large: By the end of May, the US National Bureau of Economic Research had issued 106 papers related to COVID, and that the German IZA Institute of Labor Economics had issued 60. Research most directly related to our own is that of Chiou and Tucker (2020). They find that home internet access significantly increased people's propensity to stay home, but their study considered only February and March and they omitted important explanatory variables, such as whether jobs were blue collar or white collar. Concerning the value of ICT services, Jamison and Wang (2020) study how the pandemic affects people's valuations and find about a six-fold increase during the pandemic.

Other related research has addressed workplace effects of COVID-19. Adams-Prassl, Boneva, Golin, and Rauh (2020) find that workers in jobs that require physical presence at a workplace were more likely to have reduced hours, lost employment, or lost earnings. They also find that less educated workers and women were more affected than others. Dasgupta et al. (2020) find that healthier and wealthier counties practice more social distancing than do those that are less healthy and wealthy.

Regarding more politically oriented studies, Simonov, Sacher, Dubé, and Biswas (2020) find that watching FOX News made people less likely to stay home in the early stages of the pandemic. Baccini and Brodeur (2020) study the responses of US governors to COVID-19. They find that Democratic governors and governors without term limits are more likely to implement stay-at-home orders.

3 Modeling Approach and Data

3.1 Models

To examine how broadband and other factors affect variations in residential and workplaces mobility, we use multivariate regression:

$$M_i = \gamma_1 B_i + X_i \Gamma \ + \mu_k + \epsilon_i \tag{1}$$

where the variable of interest, on the left-hand side of the equation, is either residential or workplace mobility. For each type of mobility measure, we first look at mobility change from the January benchmark week by week of second half of March and all of April, and then by every five-weekdays intervals before and after state lockdown orders came into effect in all states. Right-hand side variables are county-level characteristics obtained from the 2018 American Community Survey (ACS) as well as viral statistics for the appropriate periods. Specifically, B_i is the proportion of residents in the county with home broadband access, μ_k are the K-1 state dummies for each state and the District of Columbia, and X_i are sets of control variables, including viral cases per 100 and deaths per 100 on the first day of the week, household income (in thousands), proportion of blue collar jobs, percent of the population that is college educated, proportion Black and proportion Asian, an indicator for whether the county is in a combined statistical area, a control for age demographics, and indicators of the political party affiliation of the state governor. Regarding age demographics, for the residential mobility regressions we use the proportion aged 65 or above, and for the workplace regressions, we use proportions aged 18 or above. We also include variables for average transit time to work (in hours) and proportions of the population that take public transit to work. ϵ_i is the error term.

Our unemployment model is:

$$U_i = \eta_1 B_i + X\mathrm{H} \ + \mu_k + u_i \tag{2}$$

where U_i is the change in local area unemployment rates, from January to either March or April, obtained from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS). The estimation method is ordinary least squares, where all tables will be reported along with heteroscedasticity robust standard errors for the coefficients.

3.2 Data

We use mobility data made available by Google's "Places" services for our home and workplace models. Google collects movement data from its users and records location traffic through its "popular places" applications. It uses the same methodology to record people's tendency to stay at their residences and to visit places of work, retail and recreation centers, grocery and pharmacy stores, parks, and transit centers. The daily data show how visitors' numbers of visits to, and time spent in, places change compared to Google's chosen baseline day. The baseline day is the median value from the 5-week period Jan 3 – Feb 6, 2020. We use week-to-week changes, so the baseline days never change for our data. Baseline days do not account for seasonality. There are gaps in the data where Google believed that publishing numbers could violate privacy. Google began making this data available in March.

We restrict ourselves to looking only at residential and workplaces mobility and avoid the use of other places categories as Google warns against too many comparisons. Residential and workplaces mobility data are by day, and each day Google reports the percentage change in mobility of the day in the baseline. We aggregate data into weeks and find the average change in mobility for each week, excluding weekends. Table 1 records the weekly average changes in mobility for the last two weeks in March and all five weeks in April, and Table 2 records the data by week for workplaces. For residential mobility, due to data privacy standards, Google reports only about 1,300 counties. The picture is more complete for workplaces mobility, where Google provides data for about 2,700 counties out of some 3,000 continental U.S. counties.

[Place Table 1 about here]

Table 2 records summary statistics for the 2018 ACS data that we use. We reweighted the U.S. Census Public Use Micro-Area (PUMA) data to the county level using 2010 census population at the PUMA and county level, to match our mobility, COVID-19, and local area unemployment data. Home broadband penetration is the proportion of residents in the county that have home broadband, whether it be ADSL, cable modem, or some other technology. We define the proportion that attended college as everyone in the county that has at least attended college, regardless of whether they obtained a degree. We define metropolitan areas as all counties that fall within a combined statistical area, i.e., the county is either part of a metropolitan area or a micropolitan area as defined by the Census Bureau. Under this definition, 35% of the continental United States falls in an urbanized area. All ACS 2018 variables and definition are found in Table A2 of the Appendix.

Research by Adams-Prassl, Boneva, Golin, and Rauh (2020) implies that blue collar workers are more likely to have to show up at their workplaces during lockdowns. To test this in our dataset, we divide the occupational codes in ACS into two categories: white collar (work that is typically done in an office environment, such as management, science, arts, financial, computer, and mathematical) and blue collar, such as construction, farming, and transportation.

[Place Table 2 about here]

We use Local Area Unemployment data from the Bureau of Labor Statistics for our unemployment model. And we retrieve coronavirus cases and deaths from the New York Times COVID-19 tracking project.

4 Hypotheses and Results

4.1 Hypotheses

We explore possible connections between home broadband and residential and workplaces mobility, as well as local area unemployment. One working hypothesis is that home broadband should facilitate higher rates of staying at home. Our second working hypothesis is that the broadband should reduce the tendency to go to work. People will tend to stay home more as broadband provides a variety of online digital goods and services easily substitutable for traditional routes of leisure that usually requires stepping outside of the home. People will tend to go to their workplaces less since broadband could aid in the transition to work from home. As a first pass look at this hypothesis, one can see in figure 5 the scatterplot of residential and workplaces mobility against home broadband access, for the second week of March and the second week of April. Within a month's time, there were large changes in both types of mobilities, and just examining the pattern, there seems to be a positive correlation between residential mobility and home broadband penetration and a negative correlation between workplaces mobility and home broadband penetration. However, this might be misleading, as these simple patterns could very well be a result of, among other things, missing covariates that determine both broadband penetration and changing mobility patterns.

[Place Figure 5 about here]

As for our other explanatory variables, we expect the following to be associated with decreased mobility, i.e., greater lockdown, greater numbers of COVID cases or COVID-related deaths, higher income levels (Dasgupta et al. 2020), fewer blue-collar workers (Adams-Prassl, Boneva, Golin, and Rauh 2020), fewer working-age adults (for the workplaces model) or older age adults (for the residential model), and presence of a lockdown order. We have no prior beliefs about the effects of race, transportation, or population density.

Regarding unemployment, our working hypothesis is that home broadband facilitates people keeping their jobs during lockdowns. This would apply only to persons that are able to work remotely, which should exclude most blue-collar work.

4.2 Tendencies to Stay Home

Tables 3, 4, and 5 provide our results for people's tendencies to stay at home. Table 3 provides the calendar week regression results, controlling for state variations. Each column represents the regression results for a calendar week, beginning with the third week of March on the far left and ending with the last week of April on the far right. Table 4 provides the weekly results where data are grouped according to the number of weeks before or following lockdown. Each column represents a week. The column on the far left provides regression results for counties two weeks before their lockdown orders, and each column following is the subsequent week.

[Place Tables 3 and 4 about here]

Both tables imply that our hypothesis that home broadband would lead people to stay home more should not be accepted. The coefficient is generally not statistically significant. Even if the coefficients were statistically significant, they are small in terms of impact. We place no importance on the coefficient being negative and statistically significant for the third and fourth week of March, as well as it being negative and statistically significant for the second week prior to lockdown.

Many of our other explanatory variables had the expected correlations. More viral cases, higher incomes, fewer blue-collar jobs, and more college are significant predictors of more people staying at home. Occupation, and numbers of people over the age of 65 are the biggest determinants of whether people stay at home. For a one standard deviation rise in proportion of people over the age of 65 (a 3.8% rise), there is about a 1% decline in people's tendency to stay at home. This was not our expectation because the virus is more dangerous to older residents than younger ones. To better understand this, we looked to one of the largest retirement communities in the US -- The Villages -- that is not far from our university. The anecdotal evidence from there is that, while the community largely cancelled indoor gatherings during the lockdown, the residents continued to gather and move about outdoors, perhaps believing that this was more important to their well-being than staying inside their homes.

Proportion of county population that attended college and proportion of the county that is blue-collar also seem material: A one standard deviation rise in proportion of blue-collar workers in the county (a 3.3% rise) is associated with another 0.5% decline in people's tendency to stay at home more, and a one standard deviation rise in population that attended college (7.4%) led to a further 0.5% rise in people's tendency to stay home. While a standard deviation rise in household income accounts for roughly 1.2% of the rise in people staying at home. Race did not matter, except for being of Asian descent, which increased the likelihood of staying at home. Surprisingly, being a metropolitan area accounts for only 0.5% of the increase in tendency for residents to stay at home since January, as compared to non-metropolitan areas.

Due to Google Places Community Mobility Report having missing variables for residential mobility, resulting in only about 1,250 counties in our sample that has mobility data, one might wonder if the results we obtain are generalizable to the entire United States. In Table A2 we summarize the ACS county-level variables, by counties that have residential mobility data and by counties that do not. The noticeable difference in these two categories of counties is that counties with missing residential mobility data are much more rural (85% in rural area as compared to 33% not missing residential mobility). Also, these counties tend to be lower income, less educated and more blue-collar, but only slightly so. Because our dataset includes many rural counties, we can conclude that the residential mobility results are generalizable to the entire United States in terms of these county level statistics, although our results may not fully characterize rural areas since many rural counties are missing.

Table 5 provides results for our calendar week regressions for staying home (as does Table 4), but with regional dummy variables rather than state dummies. This checks for robustness and allows us to analyze the effects of lockdown orders and the political affiliation of state governors. The results for the other regressors align with those in Table 3. The additional information provided by Table 5 is that people were more likely to stay home if they were in states with Republican governors or a lockdown order had been issued. It is unclear why the political party matters and has the sign that it does. The Baccini and Brodeur (2020) study's finding that Democratic governors are more likely to implement stay-at-home orders than Republican governors is consistent with our Figure 2. It might be that the Republican states respond more affirmatively to lockdown because the residents have been learning from the Democrat states. Or perhaps the Republican lockdowns came at a lower economic cost, as is implied by our analysis of unemployment in section 4.3.

[Place Table 5 about here]

4.2 Tendencies to Visit Traditional Workplaces

Tables 6, 7, and 8 provide the results for our analyses of people's propensities to visit workplaces. Table 6 provides the calendar week regression results, controlling for state variations. Each column represents the regression results for a week, beginning with the third week of March on the far left and ending with the last week of April on the far right. Table 7 provides the weekly results where data are grouped according to the number of weeks before or following lockdown. Each column represents a week. The column on the far left provides regression results for counties two weeks before their lockdown orders, and each column following is the subsequent week.

[Place Tables 6 and 7 about here]

The results in Tables 6 and 7 confirm our hypothesis that people are less likely to visit their traditional workplaces if they have home broadband. So, considering state effects and county level demographics, broadband is a statistically significant predictor of decreased workplace visits. But the impact is relatively small: In the first week of April, all else equal, a one standard deviation increase in broadband penetration (11%) from county to county only accounts for 0.7% decrease in workplace visits. Considering the median change in workplaces mobility is about a 40%

decrease week to week in April, County level differences in broadband access accounts for only a small part of that change.

It is hard to know from these results if home broadband affects social distancing. Even though Tables 6 and 7 indicate that the presence of home broadband leads people to go to work less, Tables 3 and 4 imply that these people did not spend more time at home, perhaps implying that they went someplace besides work. It might be that they took more walks, went for drives, or did outings to help themselves or others deal with COVID. We cannot tell from the data.

Other explanatory variables also had expected impacts. More viral cases, higher incomes, fewer blue-collar workers, and more college are significant predictors of fewer people going to work. These variables seem to explain changes in workplace visits. Dividing occupations into blue collar and white-collar jobs, we see that a one standard deviation increase in the percentage of workers that are blue collar has an impact of decreasing workplace visits by 1.5%. Furthermore, going from a metropolitan area to a non-metropolitan area, workplace mobility increases by 3.25% in the first week of April. In visit to workplace regressions, proportion of Black residents became a significant explanatory variable, supporting a belief that Blacks were more likely to visit traditional workplaces than other races. We added additional regressors transit time to work and proportion of residents take public transit to work. Every ten minutes of average increase in transit time decreases people's tendency to go to work by about 2% week by week in late March and April, while one standard deviation increase in people taking transit decreases visit to workplaces by about 0.5%, but only since the second week of April.

Table 8 presents calendar week regressions for workplace visits with regional dummies rather than state dummy variables. This checks for robustness and allows us to study the effects of the governors' political parties and lockdowns. The signs and significance of the explanatory variables remain the same as in Tables 6 and 7 except the effects of age lost statistical significance some weeks.

Having a Republican governor was associated with people being more likely to go to work. If having a Republican governor is correlated with a higher portion of residents being Republicans, then our finding is consistent with numerous news accounts of Republicans being more defiant of lockdown orders than Democrats. Lockdown orders led to more people not going to their workplaces, but as Figure 4 shows, people began going to work less even before lockdown orders were given.

[Place Table 8 about here]

4.3 Unemployment

To fully understand changes in visits to work, we examine changes in unemployment rates. Declines in workplace visits might be understood as people complying with lockdowns, but it might also be that people have lost their jobs. Table 9 reports summary statistics for changes in unemployment rates since January. The average unemployment rate in March for all counties was about 4.8%, which is not much of a change since January (a 0.2% increase).

[Place Table 9 and 10 about here]

Table 10 provides our results. Home broadband is associated with higher unemployment rates. This is an unexpected result. It might be that home broadband and unemployment are both correlated with a third variable that we omit from our model, but we are unsure what that might be. Perhaps the explanation can be found in considering that a change in unemployment reflects movement in the intersection of supply and demand for employment. It seems unlikely that home broadband affects the demand for employment, except to the extent that employers might insist that employees have it if they are working from home. If that effect dominates other effects, we expect a negative correlation between home broadband and unemployment, which we do not have. It could also be that home broadband affects the supply of employment, i.e., people's willingness to be employed. It might be that home broadband gives people opportunities for alternative employment that is unreported in the statistics or gives people alternative uses of their time (e.g., video streaming increased significantly during the pandemic). Since we are unable to identify the underlying cause for the positive correlation between home broadband and unemployment, we simply note that our hypothesis of a negative correlation is unsupported, i.e., home broadband did not help people keep their jobs, which may in part explain why home broadband is associated with fewer workplace visits.

Table 10 also shows the results for other county-level characteristics. Rural areas fare better than metropolitan areas, which have their unemployment rates decrease an additional 1.1 percentage points since January. A one standard deviation increase in proportion of the population blue-collar leads to about a 2% increase in the unemployment rate. Unemployment rates tend to have risen higher also in counties with a higher number of COVID-19 cases in April. Places of higher household income tends to have less Unemployment in April, as are places that tend to have less of their workers taking public transit to work. At least one regression for April found less unemployment rate rises in counties with higher rates of death, something that did not hold in the other models. This might reflect employment responding more than our mobility measures to the severity of COVID outbreaks.

Effects of other explanatory variables are sometimes different for unemployment than for our mobility models. The effect of blue-collar employment changes over time: In March, the effect is to decrease unemployment, but in April the effect is to increase it. This implies that blue collar workers were more likely to keep their jobs in the early part of the pandemic, but less likely as time passed and more lockdowns occurred. Blacks were less likely to be unemployed, which aligns with their greater propensity to go to workplaces. Counties in states with Republican governors experienced higher unemployment in March, but lower unemployment in April. The effects were small, but together with the workplaces results, it appears that while Republican governors kept more people going to work in March and April, residents were more likely to lose their jobs in March, but then more than made up for that in April.

4.4 Effects of Lockdown Orders

Although lockdown orders are not the focus of this paper, the results provide some insights into their impacts and people's compliance. Tables 4 and 7 provide results relative to the timing of lockdown orders. Interestingly, for either workplace visits or time at home, the transition seems to be completed just before state lockdowns came into effect, suggesting that many people and businesses/institutions were voluntarily locking down and people were staying at home even before official state mandates. This is evident in Figure 6, where we plotted changes in residential and workplaces mobility for every day before or after all state lockdowns. We see that most states had already completed transitions before the orders were in place. This is not to say that mandated lockdowns were not effective at all; the fact that mobility curves stayed flat for the entirety of April toward the beginning of May might result from state mandated lockdowns.

5 Discussion and Conclusion

To some people's perspectives, the spread of COVID-19 was fast and unexpected. Mobility responses were similarly fast. Within half a month, from the middle of March to the beginning of April, staying at home rose by 15% and visiting workplaces declined by 40%. These changes stayed at their levels for most of the month of April. All these changes seem to be voluntary, occurring even before state lockdowns or stay-at-home orders were officially in place.

Our main results for both staying home and visiting workplaces explain that the bulk of the reasons why people decide to stay home has to do with factors such as age, type of occupation, and level of education, not broadband. Home broadband's impact is at best small even when statistically significant, although that is rare. Specifically, though we do observe an initially large positive simple correlation between home broadband penetration and people staying at home, as well as a large negative simple correlation between broadband and people visiting workplaces, we show these simple correlations are misleading, after considering county level demographic variables, particularly income, percentage blue-collar, percentage that attended college, metropolitan status and age. Broadband penetration itself seems to explain only a small portion of the changes in mobility trends in the U.S. in the second half of March and all of April.

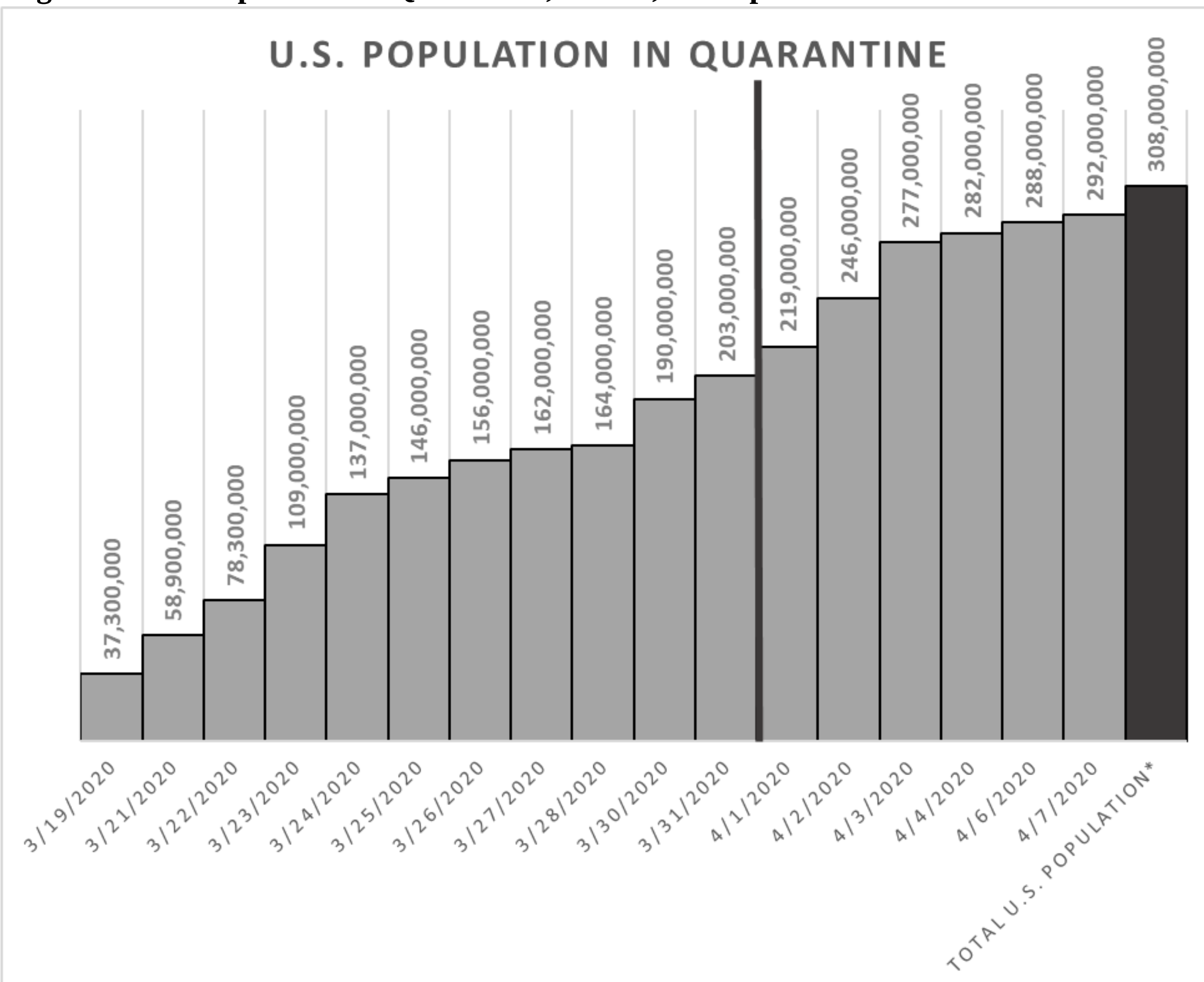
In terms of people's likelihood to observe social distancing, we found that areas with older populations or lower income tend to observe staying at home less. This is sometimes attributed to the presence of multigenerational homes in the case of lower income households, and to lifestyle choices in the case of older populations. Future policy choices should consider these differences.

Even though broadband did not play a significant role in mobility, this does not imply that it is unimportant. In Jamison and Wang (2020), we found that for the month of March the median consumer valuation of digital goods and services rose by some 600%. So as people stay home more, digital goods and services create more value. However, one cannot draw from that conclusion then that home broadband access will lead to more observance of social distancing measures; that has more to do with the demographics.

Further research is needed. Though we were able to evaluate the impact of broadband on people's tendency to stay at home and go to work, we did not examine other movements, such as visiting retail and recreational locations. More research on broadband and unemployment is also needed. While in April places that had a higher home broadband penetration suffered more in terms of unemployment woes, the linkage is unclear. Also, while we measure behaviors in the early stages of the pandemic, it will be important to see behavior adaptations as the pandemic further unfolds.

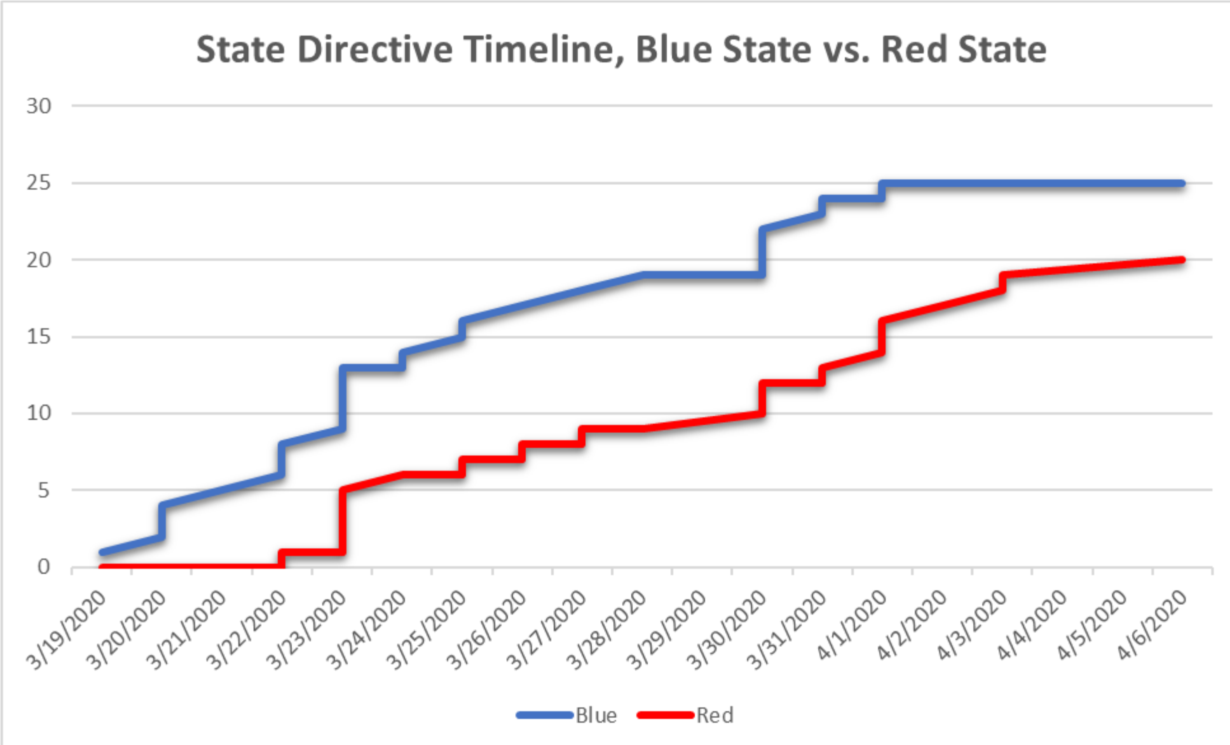
Tables and Figures

Figure 1: U.S. Population in Quarantine, March, and April



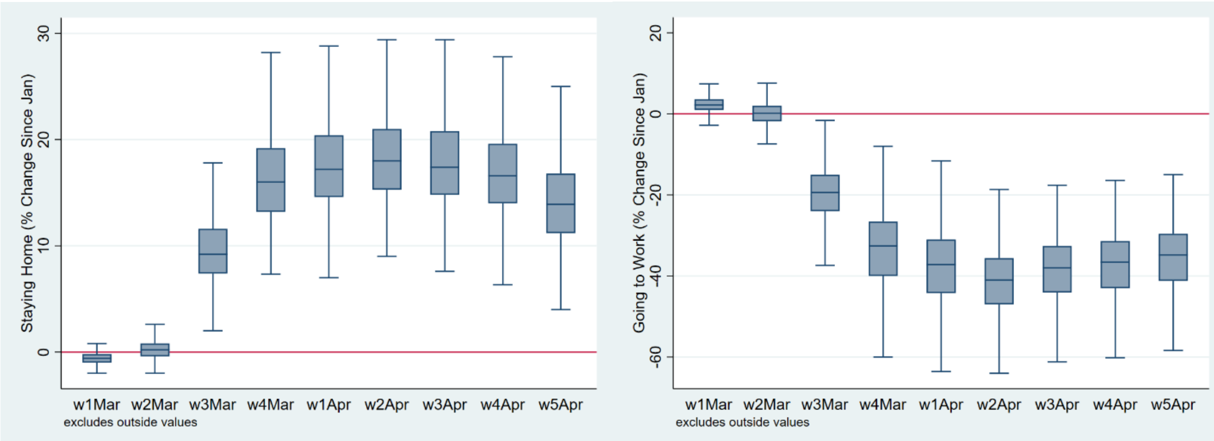
*Total United State Population minus Alaska, Puerto Rico, and minor islands. United States Populations are 2020 estimates based on the 2010 U.S. Census. By the end of March, about two-thirds of Americans in the Continental United States are in State mandated quarantine.

Figure 2: State Directive Timeline



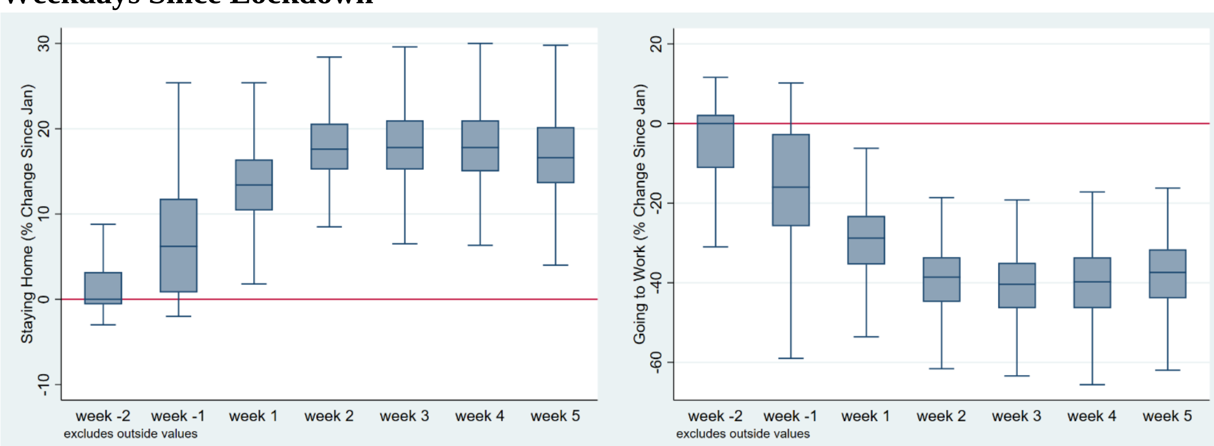
25 Blue States (plus District of Columbia) and 25 Red States (as defined by party of State governor) in the Continental United States. Four "Red" States never had lockdown or social distancing directives: Arkansas, Iowa, Nebraska, North Dakota, and Wyoming.

Figure 3: Workplace Visit and time spent at home Percent Changes from Baseline, Weekly (weekdays only)



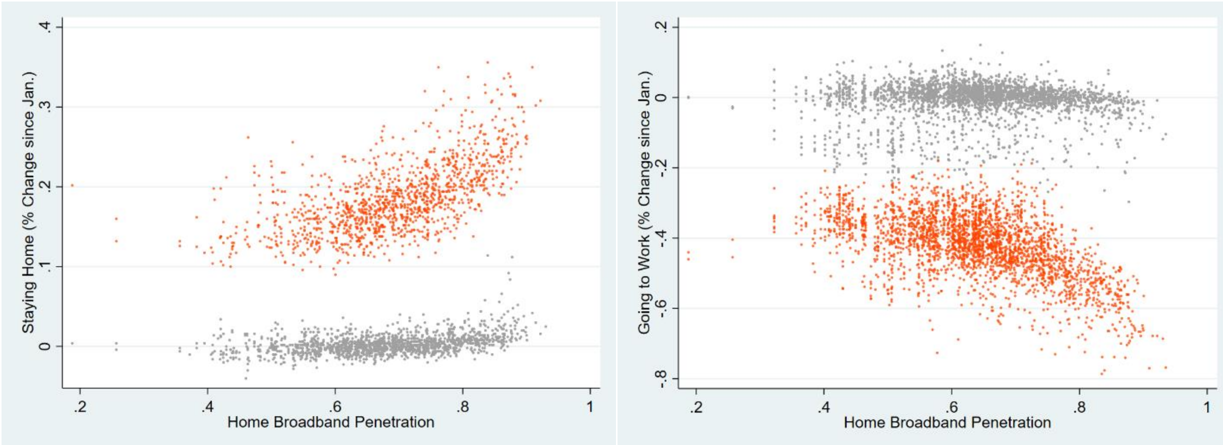
Weekly Boxplot of county-level residential and workplaces mobility for every week of March and April, excluding weekends. Mobility data obtained from Google mobility report.

Figure 4: Workplace Visit and time spent at home Percent Changes from Baseline, Weekdays Since Lockdown



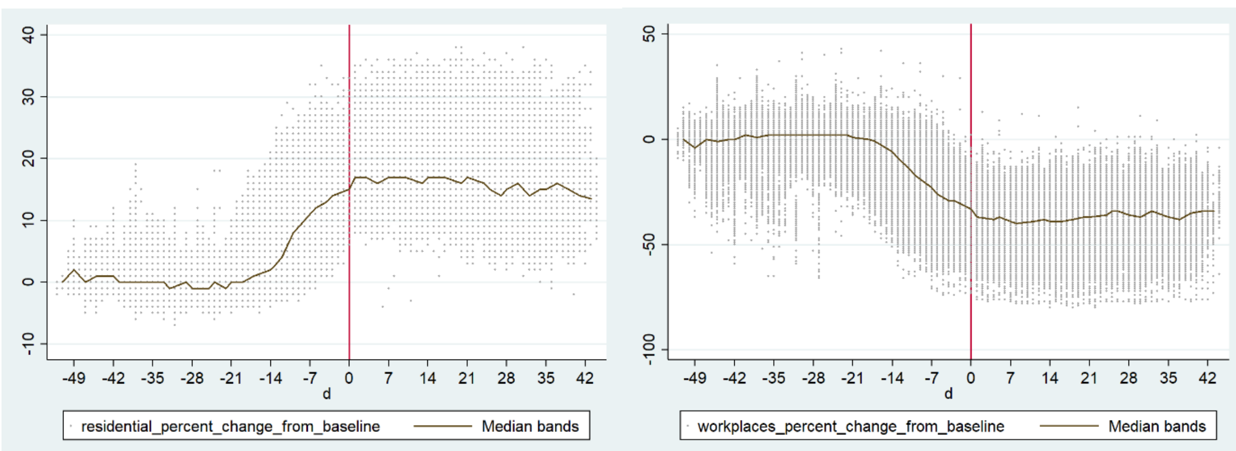
Boxplot of county-level residential and workplaces mobility every 5 weekdays, for the two intervals (weekdays) prior to the effective date of state lockdown orders, and four intervals after state lockdown orders came into effect.

Figure 5: Scatterplots of Time spent at home and visits to workplaces versus home broadband



Scatterplot of county-level time at home and visits to workplaces, for the 2nd week of March (Grey dots) and 2nd week of April (Orange dots). One can see a dramatic change in either types of mobility from the week just before the outbreak to the height of mobility restrictions in the middle of April. Counties with varying levels of home broadband penetration seems to have responded with varying degrees of mobility changes.

Figure 6: Time at home and visits to workplace Changes, daily since lockdown orders



Daily county-level change in residential and workplaces mobility, for every day prior to effective state lockdown orders up to 49 days prior and for every day after state lockdown orders up to 42 days since. Percentage change in mobility from January in the y-axis.

Table 1: Summary Statistics of Mobility March and April

Time at Home by Weeks in March and April (Weekdays only)			
Weeks	**Observations**	**Mean**	**Standard Deviation**
3rd Week of March	1,445	0.098	0.036
4th Week of March	1,312	0.165	0.044
1st Week of April	1,278	0.178	0.044
2nd Week of April	1,264	0.185	0.044
3rd Week of April	1,271	0.181	0.046
4th Week of April	1,282	0.172	0.044
5th Week of April	1,306	0.145	0.046
Visits to Workplaces by Weeks in March and April (Weekdays only)			
3rd Week of March	2,697	-0.203	0.081
4th Week of March	2,713	-0.339	0.100
1st Week of April	2,742	-0.382	0.098
2nd Week of April	2,755	-0.419	0.090
3rd Week of April	2,760	-0.390	0.091
4th Week of April	2,765	-0.379	0.091
5th Week of April	2,765	-0.360	0.091

Table 2: Summary Statistics

Variables	Observations	Mean	Standard Deviation
Home Broadband Penetration	3,113	0.631	0.115
Household Income	3,113	79368.2	18199.5
Proportion Blue-Collar	3,113	0.161	0.032
Proportion attended College	3,113	0.419	0.073
Proportion Black	3,113	.087	0.132
Proportion Asian	3,113	.0154	0.029
Proportion Metropolitan	3,113	0.348	0.476
Average Transit Time to Work (Hour)	3,113	0.133	0.047
Proportion Take Public Transit to Work	3,113	0.005	0.016
Proportion 18 and above	3,113	0.769	0.027
Proportion 65 and above	3,113	.170	0.033

Table 3: Weekly Regression of Time at Home: State Dummies

VARIABLES	3rd Mar. residential	4th Mar. residential	1st Apr. residential	2nd Apr. residential	3rd Apr. residential	4th Apr. residential	5th Apr. residential
Broadband Pen.	-0.0219***	-0.00605	-0.00349	0.00449	0.00445	0.000374	0.00567
	(0.00677)	(0.00914)	(0.00904)	(0.00928)	(0.00986)	(0.00887)	(0.00889)
Cases per 100	1.398***	0.0436	0.0447***	0.0616***	0.0394***	0.0136**	0.0117**
	(0.255)	(0.0471)	(0.0151)	(0.0105)	(0.00658)	(0.00662)	(0.00468)
Deaths per 100	-6.782***	1.857	-0.602	-0.779***	-0.376***	-0.0874	-0.0736
	(2.262)	(1.540)	(0.565)	(0.172)	(0.0753)	(0.0779)	(0.0569)
Log HH income	0.0611***	0.0655***	0.0621***	0.0575***	0.0601***	0.0603***	0.0668***
	(0.00421)	(0.00519)	(0.00534)	(0.00544)	(0.00551)	(0.00531)	(0.00509)
Prop. Blue-collar	-0.125***	-0.125***	-0.0824**	-0.105***	-0.0911**	-0.129***	-0.115***
	(0.0227)	(0.0364)	(0.0378)	(0.0404)	(0.0401)	(0.0374)	(0.0355)
Prop. College	0.0688***	0.0834***	0.102***	0.0721***	0.0956***	0.0899***	0.0766***
	(0.0126)	(0.0171)	(0.0182)	(0.0191)	(0.0197)	(0.0181)	(0.0175)
Prop. Black	-0.00470	-0.00453	-0.00845	-0.00973	-0.00955	-0.00120	0.00101
	(0.00495)	(0.00713)	(0.00749)	(0.00799)	(0.00975)	(0.00754)	(0.00725)
Prop. Asian	0.251***	0.256***	0.282***	0.286***	0.291***	0.297***	0.303***
	(0.0237)	(0.0228)	(0.0266)	(0.0286)	(0.0277)	(0.0254)	(0.0242)
Metro. Area	0.00375***	0.00527***	0.00590***	0.00756***	0.00437***	0.00599***	0.00530***
	(0.000994)	(0.00131)	(0.00136)	(0.00141)	(0.00151)	(0.00137)	(0.00133)
Prop. over 65	-0.160***	-0.262***	-0.291***	-0.292***	-0.300***	-0.284***	-0.269***
	(0.0192)	(0.0249)	(0.0253)	(0.0251)	(0.0265)	(0.0250)	(0.0239)
Constant	-0.580***	-0.573***	-0.534***	-0.450***	-0.510***	-0.508***	-0.610***
	(0.0460)	(0.0599)	(0.0615)	(0.0638)	(0.0641)	(0.0617)	(0.0586)
Observations	1,254	1,254	1,254	1,254	1,254	1,254	1,254
R-squared	0.850	0.844	0.836	0.829	0.833	0.841	0.852

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression for Time at Home for days Since State Lockdowns: State Dummies

VARIABLES	6 to 10 Days Prior residential	5 to 1 Day Prior residential	1 to 5 Days Since residential	6 to 10 Days Since residential	11 to 15 Days Since residential	16 to 20 Days Since residential
Broadband Pen.	0.00851	-0.00579	-0.00225	0.00586	0.00203	0.00709
	(0.00821)	(0.00889)	(0.00975)	(0.0104)	(0.00967)	(0.00978)
Cases per 100	0.882***	1.214***	1.330***	0.0398***	0.0549***	0.0396***
	(0.323)	(0.335)	(0.337)	(0.0144)	(0.0171)	(0.0143)
Deaths per 100	4.065	-6.623	-9.925**	-0.471	-0.955	-0.552
	(7.037)	(5.584)	(4.896)	(0.535)	(0.598)	(0.528)
Log HH income	0.0377***	0.0590***	0.0638***	0.0636***	0.0649***	0.0668***
	(0.00470)	(0.00484)	(0.00526)	(0.00559)	(0.00551)	(0.00561)
Prop. Blue-collar	-0.0873***	-0.172***	-0.0952**	-0.0995**	-0.109***	-0.104***
	(0.0267)	(0.0349)	(0.0408)	(0.0428)	(0.0397)	(0.0392)
Prop. College	0.0698***	0.0828***	0.0847***	0.0794***	0.0721***	0.0686***
	(0.0155)	(0.0166)	(0.0185)	(0.0206)	(0.0195)	(0.0193)
Prop. Black	-0.00775	-0.00563	-0.00462	-0.000902	0.00390	0.00287
	(0.00638)	(0.00703)	(0.00775)	(0.00864)	(0.00791)	(0.00769)
Prop. Asian	0.0673***	0.192***	0.261***	0.276***	0.289***	0.292***
	(0.0206)	(0.0195)	(0.0243)	(0.0265)	(0.0274)	(0.0264)
Metro. Area	0.00129	0.00458***	0.00607***	0.00588***	0.00642***	0.00580***
	(0.00114)	(0.00132)	(0.00145)	(0.00159)	(0.00147)	(0.00145)
Prop. over 65	-0.201***	-0.280***	-0.275***	-0.299***	-0.287***	-0.283***
	(0.0210)	(0.0255)	(0.0253)	(0.0266)	(0.0257)	(0.0264)
Constant	-0.276***	-0.476***	-0.525***	-0.543***	-0.557***	-0.607***
	(0.0517)	(0.0571)	(0.0622)	(0.0657)	(0.0634)	(0.0645)
Observations	1,150	1,150	1,150	1,150	1,150	1,150
R-squared	0.938	0.863	0.813	0.814	0.845	0.866

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Weekly Regressions of Time at Home: Region Dummies

VARIABLES	3rd Mar. residential	4th Mar. residential	1st Apr. residential	2nd Apr. residential	3rd Apr. residential	4th Apr. residential	5th Apr. residential
Broadband Pen.	-0.0170**	0.00891	-0.00438	0.00868	0.0117	0.0128	0.0179*
	(0.00662)	(0.00918)	(0.00961)	(0.0101)	(0.0109)	(0.00971)	(0.00951)
Cases per 100	1.432***	0.0275	0.0339**	0.0602***	0.0418***	0.0151**	0.0132***
	(0.307)	(0.0380)	(0.0147)	(0.0112)	(0.00780)	(0.00655)	(0.00471)
Deaths per 10	-7.687***	2.482*	-0.0196	-0.727***	-0.378***	-0.0798	-0.0708
	(2.797)	(1.422)	(0.590)	(0.198)	(0.0991)	(0.0884)	(0.0658)
Log HH income	0.0722***	0.0745***	0.0716***	0.0688***	0.0693***	0.0650***	0.0743***
	(0.00425)	(0.00507)	(0.00500)	(0.00516)	(0.00540)	(0.00525)	(0.00522)
Prop. Blue-collar	-0.149***	-0.167***	-0.122***	-0.131***	-0.151***	-0.166***	-0.156***
	(0.0228)	(0.0340)	(0.0359)	(0.0372)	(0.0376)	(0.0349)	(0.0342)
Prop. college	0.0416***	0.0294*	0.0785***	0.0406**	0.0660***	0.0668***	0.0489***
	(0.0112)	(0.0159)	(0.0168)	(0.0168)	(0.0180)	(0.0164)	(0.0158)
Prop. Black	-0.00702	0.00137	-0.0115	-0.00354	-0.0172**	0.000665	0.000644
	(0.00455)	(0.00656)	(0.00723)	(0.00737)	(0.00849)	(0.00731)	(0.00721)
Prop. Asian	0.138***	0.151***	0.157***	0.195***	0.170***	0.196***	0.197***
	(0.0414)	(0.0313)	(0.0289)	(0.0328)	(0.0296)	(0.0298)	(0.0321)
Metro. Area	0.00475***	0.00764***	0.00750***	0.00929***	0.00601***	0.00810***	0.00733***
	(0.00109)	(0.00151)	(0.00158)	(0.00164)	(0.00181)	(0.00160)	(0.00154)
Prop. over 65	-0.188***	-0.232***	-0.298***	-0.278***	-0.282***	-0.249***	-0.231***
	(0.0180)	(0.0215)	(0.0240)	(0.0239)	(0.0252)	(0.0225)	(0.0216)
Republican	-0.00421***	-0.00611***	0.000671	-0.00177	-0.00411***	-0.00470***	-0.00520***
	(0.000972)	(0.00137)	(0.00171)	(0.00148)	(0.00159)	(0.00148)	(0.00144)
State Lockdown	N/A	0.0193***	0.0165***	0.0241***	0.0156***	0.0184***	0.0201***
		(0.00156)	(0.00174)	(0.00203)	(0.00276)	(0.00213)	(0.00205)
Constant	-0.660***	-0.628***	-0.598***	-0.572***	-0.578***	-0.543***	-0.673***
	(0.0464)	(0.0578)	(0.0575)	(0.0593)	(0.0609)	(0.0593)	(0.0594)
Observations	1,254	1,254	1,254	1,254	1,254	1,254	1,254
R-squared	0.792	0.772	0.751	0.743	0.733	0.754	0.777

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Weekly Regressions of Visits to Workplaces: State Dummies

VARIABLES	3rd Mar. workplaces	4th Mar. workplaces	1st Apr. workplaces	2nd Apr. workplaces	3rd Apr. workplaces	4th Apr. workplaces	5th Apr. workplaces
Broadband Pen.	-0.000289	-0.0624***	-0.0601***	-0.0641***	-0.0633***	-0.0594***	-0.0693***
	(0.0140)	(0.0159)	(0.0155)	(0.0147)	(0.0154)	(0.0150)	(0.0152)
Cases per 100	-3.013***	-0.360*	-0.122*	-0.135***	-0.108***	-0.0429***	-0.0232***
	(0.506)	(0.203)	(0.0657)	(0.0233)	(0.0181)	(0.0137)	(0.00851)
Deaths per 100	4.479	-2.173	-0.305	1.519***	1.091***	0.302*	0.115
	(3.419)	(2.395)	(1.228)	(0.456)	(0.213)	(0.173)	(0.119)
Log HH income	-0.0199	-0.0109	-0.000206	-0.00441	0.000154	-0.00201	-0.00880
	(0.0129)	(0.0137)	(0.0139)	(0.0126)	(0.0130)	(0.0126)	(0.0126)
Prop. Blue-collar	0.533***	0.469***	0.368***	0.334***	0.414***	0.385***	0.345***
	(0.0579)	(0.0623)	(0.0641)	(0.0596)	(0.0608)	(0.0582)	(0.0583)
Prop. College	-0.217***	-0.317***	-0.366***	-0.297***	-0.318***	-0.349***	-0.345***
	(0.0354)	(0.0389)	(0.0387)	(0.0360)	(0.0372)	(0.0362)	(0.0372)
Prop. Black	0.0295**	0.0369***	0.0554***	0.0677***	0.0248*	0.0334***	0.0247**
	(0.0116)	(0.0141)	(0.0138)	(0.0127)	(0.0138)	(0.0126)	(0.0125)
Prop. Asian	-0.641***	-0.588***	-0.610***	-0.578***	-0.576***	-0.606***	-0.627***
	(0.0642)	(0.0582)	(0.0576)	(0.0519)	(0.0529)	(0.0538)	(0.0550)
Metro. Area	-0.0205***	-0.0282***	-0.0326***	-0.0301***	-0.0285***	-0.0322***	-0.0318***
	(0.00228)	(0.00257)	(0.00254)	(0.00240)	(0.00248)	(0.00244)	(0.00244)
Transit time	-0.225***	-0.253***	-0.240***	-0.184***	-0.201***	-0.210***	-0.201***
	(0.0305)	(0.0333)	(0.0332)	(0.0311)	(0.0317)	(0.0311)	(0.0309)
Public Transit	-0.258***	-0.120	-0.220*	-0.359***	-0.374***	-0.349***	-0.366***
	(0.0962)	(0.109)	(0.115)	(0.0861)	(0.0799)	(0.0828)	(0.0855)
Prop. Above 18	0.371***	0.366***	0.428***	0.396***	0.403***	0.441***	0.499***
	(0.0713)	(0.0778)	(0.0765)	(0.0719)	(0.0741)	(0.0714)	(0.0718)
Constant	-0.190	-0.335*	-0.512***	-0.520***	-0.529***	-0.513***	-0.447***
	(0.165)	(0.176)	(0.179)	(0.163)	(0.167)	(0.161)	(0.161)
Observations	2,696	2,696	2,696	2,696	2,696	2,696	2,696
R-squared	0.662	0.707	0.704	0.688	0.688	0.701	0.704

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regressions for Visits to Workplaces days Since State Lockdowns: State Dummies

VARIABLES	6 to 10 Days Prior workplaces	5 to 1 Day Prior workplaces	1 to 5 Days Since workplaces	6 to 10 Days Since workplaces	11 to 15 Days Since workplaces	16 to 20 Days Since workplaces
Broadband Pen.	-0.0226	-0.0442***	-0.0512***	-0.0596***	-0.0656***	-0.0644***
	(0.0155)	(0.0158)	(0.0160)	(0.0159)	(0.0158)	(0.0164)
Cases per 100	-2.421***	-3.366***	-3.177***	-0.0877	-0.0928*	-0.0816
	(0.426)	(0.525)	(0.579)	(0.0596)	(0.0559)	(0.0513)
Deaths per 10	-9.208	3.413	4.986	-0.658	-0.175	-0.342
	(5.678)	(3.916)	(4.589)	(1.103)	(1.048)	(1.035)
Log HH income	0.0194	-0.00201	-0.00828	-0.00274	-0.00166	-0.00473
	(0.0132)	(0.0133)	(0.0131)	(0.0136)	(0.0135)	(0.0134)
Prop. Blue-collar	0.366***	0.566***	0.373***	0.365***	0.359***	0.365***
	(0.0535)	(0.0620)	(0.0643)	(0.0643)	(0.0622)	(0.0632)
Prop. College	-0.308***	-0.294***	-0.337***	-0.329***	-0.340***	-0.353***
	(0.0381)	(0.0378)	(0.0390)	(0.0382)	(0.0379)	(0.0385)
Prop. Black	0.0450***	0.0391***	0.0475***	0.0387***	0.0245*	0.0259*
	(0.0137)	(0.0138)	(0.0136)	(0.0142)	(0.0138)	(0.0137)
Prop. Asian	-0.342***	-0.579***	-0.608***	-0.600***	-0.594***	-0.596***
	(0.0738)	(0.0597)	(0.0561)	(0.0544)	(0.0551)	(0.0564)
Metro. Area	-0.0123***	-0.0266***	-0.0284***	-0.0275***	-0.0273***	-0.0293***
	(0.00226)	(0.00255)	(0.00269)	(0.00264)	(0.00257)	(0.00263)
Transit time	-0.231***	-0.271***	-0.200***	-0.194***	-0.217***	-0.210***
	(0.0323)	(0.0336)	(0.0336)	(0.0332)	(0.0328)	(0.0331)
Public Transit	-0.0760	-0.219**	-0.315***	-0.283***	-0.293***	-0.327***
	(0.114)	(0.0867)	(0.0822)	(0.100)	(0.0983)	(0.0947)
Prop. Above 18	0.484***	0.338***	0.377***	0.405***	0.449***	0.482***
	(0.0687)	(0.0759)	(0.0784)	(0.0767)	(0.0754)	(0.0757)
Constant	-0.786***	-0.486***	-0.457***	-0.499***	-0.521***	-0.485***
	(0.159)	(0.170)	(0.171)	(0.176)	(0.173)	(0.172)
Observations	2,367	2,367	2,367	2,367	2,367	2,367
R-squared	0.882	0.732	0.649	0.670	0.730	0.724

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Weekly Regressions of Visits to Workplaces: Region Dummies

VARIABLES	3rd Mar. workplaces	4th Mar. workplaces	1st Apr. workplaces	2nd Apr. workplaces	3rd Apr. workplaces	4th Apr. workplaces	5th Apr. workplaces
Broadband Pen.	0.0281**	-0.0586***	-0.0504***	-0.0958***	-0.0860***	-0.0880***	-0.0952***
	(0.0132)	(0.0153)	(0.0158)	(0.0151)	(0.0154)	(0.0150)	(0.0150)
Cases per 100	-3.241***	-0.309	-0.106	-0.141***	-0.113***	-0.0467***	-0.0232***
	(0.531)	(0.218)	(0.0711)	(0.0227)	(0.0179)	(0.0127)	(0.00827)
Deaths per 10	5.360**	-3.065	-1.667	1.357**	1.097***	0.295	0.0820
	(2.548)	(2.932)	(1.319)	(0.587)	(0.259)	(0.207)	(0.148)
Log HH income	-0.0605***	-0.0278**	-0.0151	-0.00727	0.00385	-0.00128	-0.0145
	(0.0121)	(0.0130)	(0.0131)	(0.0121)	(0.0123)	(0.0121)	(0.0121)
Prop. Blue-collar	0.599***	0.502***	0.439***	0.353***	0.460***	0.452***	0.424***
	(0.0551)	(0.0600)	(0.0614)	(0.0587)	(0.0587)	(0.0570)	(0.0569)
Prop. college	-0.144***	-0.139***	-0.208***	-0.129***	-0.185***	-0.199***	-0.193***
	(0.0299)	(0.0362)	(0.0353)	(0.0334)	(0.0339)	(0.0331)	(0.0334)
Prop. Black	0.0503***	0.0412***	0.0423***	0.0441***	0.0344***	0.0465***	0.0386***
	(0.0102)	(0.0119)	(0.0128)	(0.0114)	(0.0114)	(0.0111)	(0.0112)
Prop. Asian	-0.348***	-0.313***	-0.386***	-0.398***	-0.373***	-0.398***	-0.408***
	(0.110)	(0.0946)	(0.0894)	(0.0825)	(0.0805)	(0.0844)	(0.0882)
Metro. Area	-0.0245***	-0.0377***	-0.0406***	-0.0374***	-0.0364***	-0.0398***	-0.0391***
	(0.00252)	(0.00287)	(0.00295)	(0.00278)	(0.00279)	(0.00276)	(0.00274)
Transit time	-0.172***	-0.294***	-0.269***	-0.231***	-0.255***	-0.260***	-0.250***
	(0.0307)	(0.0341)	(0.0345)	(0.0339)	(0.0344)	(0.0335)	(0.0335)
Public Transit	-0.408***	-0.235**	-0.242**	-0.354***	-0.450***	-0.426***	-0.461***
	(0.127)	(0.119)	(0.116)	(0.0942)	(0.0874)	(0.0934)	(0.101)
Prop. Above 18	0.287***	-0.00282	0.165**	0.0376	0.0223	0.0637	0.135**
	(0.0620)	(0.0684)	(0.0693)	(0.0634)	(0.0632)	(0.0611)	(0.0609)
Republican	0.00585***	0.00945***	-0.0102***	0.00530*	0.00993***	0.00813***	0.0127***
	(0.00226)	(0.00280)	(0.00391)	(0.00282)	(0.00284)	(0.00277)	(0.00274)
State Lockdown	N/A	-0.0613***	-0.0510***	-0.0465***	-0.0293***	-0.0310***	-0.0256***
		(0.00344)	(0.00399)	(0.00402)	(0.00432)	(0.00389)	(0.00375)
Constant	0.205	0.0167	-0.240	-0.247*	-0.344**	-0.298**	-0.187
	(0.153)	(0.162)	(0.164)	(0.150)	(0.152)	(0.148)	(0.149)
Observations	2,696	2,696	2,696	2,696	2,696	2,696	2,696
R-squared	0.569	0.606	0.576	0.549	0.561	0.583	0.597

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Unemployment Summary Statistics

	Mean	Standard Deviation	Observations
March			
Unemployment Rate	0.0481	0.0204	3,090
Change since Jan.	0.0018	0.0472	*-*
April			
Unemployment Rate	0.1248	0.0525	3,103
Change since Jan.	0.0784	0.0472	*-*

Table 10: Changes in Unemployment Rate: April versus March

VARIABLES	March Change in Unemployment Rate since January	March Change in Unemployment Rate since January	April Change in Unemployment Rate since January	April Change in Unemployment Rate since January
Broadband Pen.	0.00428***	0.000964	0.0519***	0.0433***
	(0.00149)	(0.00205)	(0.00832)	(0.0104)
Cases per 100	-0.0332	0.105	0.0308***	0.0314***
	(0.0604)	(0.0683)	(0.00852)	(0.00967)
Deaths per 10	2.462	0.599	-0.289***	-0.227
	(1.808)	(1.103)	(0.102)	(0.138)
Log HH Income	-0.000368***	0.000278	-0.00200***	-0.00170**
	(0.000123)	(0.000172)	(0.000714)	(0.000778)
Prop. Blue-collar	-0.00774*	-0.0335***	0.0790***	0.110***
	(0.00461)	(0.00670)	(0.0298)	(0.0321)
Prop. College	-0.000503	-0.0197***	0.0204	-0.0995***
	(0.00322)	(0.00399)	(0.0193)	(0.0203)
Prop. Black	0.000731	-0.00959***	-0.0141*	-0.0182***
	(0.00123)	(0.00164)	(0.00735)	(0.00693)
Prop. Asian	0.000284	0.0159*	0.0144	0.120***
	(0.00806)	(0.00875)	(0.0341)	(0.0369)
Metro. Area	0.000482**	0.000473	0.0117***	0.0201***
	(0.000199)	(0.000370)	(0.00145)	(0.00190)
Transit time	0.0230***	0.00408	-0.0394	-0.163***
	(0.00683)	(0.00853)	(0.0478)	(0.0524)
Public Transit	0.00818***	-0.00233	0.0916***	0.153***
	(0.00296)	(0.00443)	(0.0178)	(0.0215)
Prop. Above 18	-0.0101	-0.0240***	0.197***	0.561***
	(0.00704)	(0.00817)	(0.0367)	(0.0362)
Republican Gov.		0.00185***		-0.00346*
		(0.000306)		(0.00178)
State Dummies	YES	NO	YES	NO
Region Dummies	NO	Yes	NO	YES
Constant	0.00509	0.0298***	-0.105***	-0.371***
	(0.00552)	(0.00658)	(0.0289)	(0.0285)
Observations	3,090	3,090	3,103	3,103
R-squared	0.754	0.264	0.575	0.182

Robust std. errs. in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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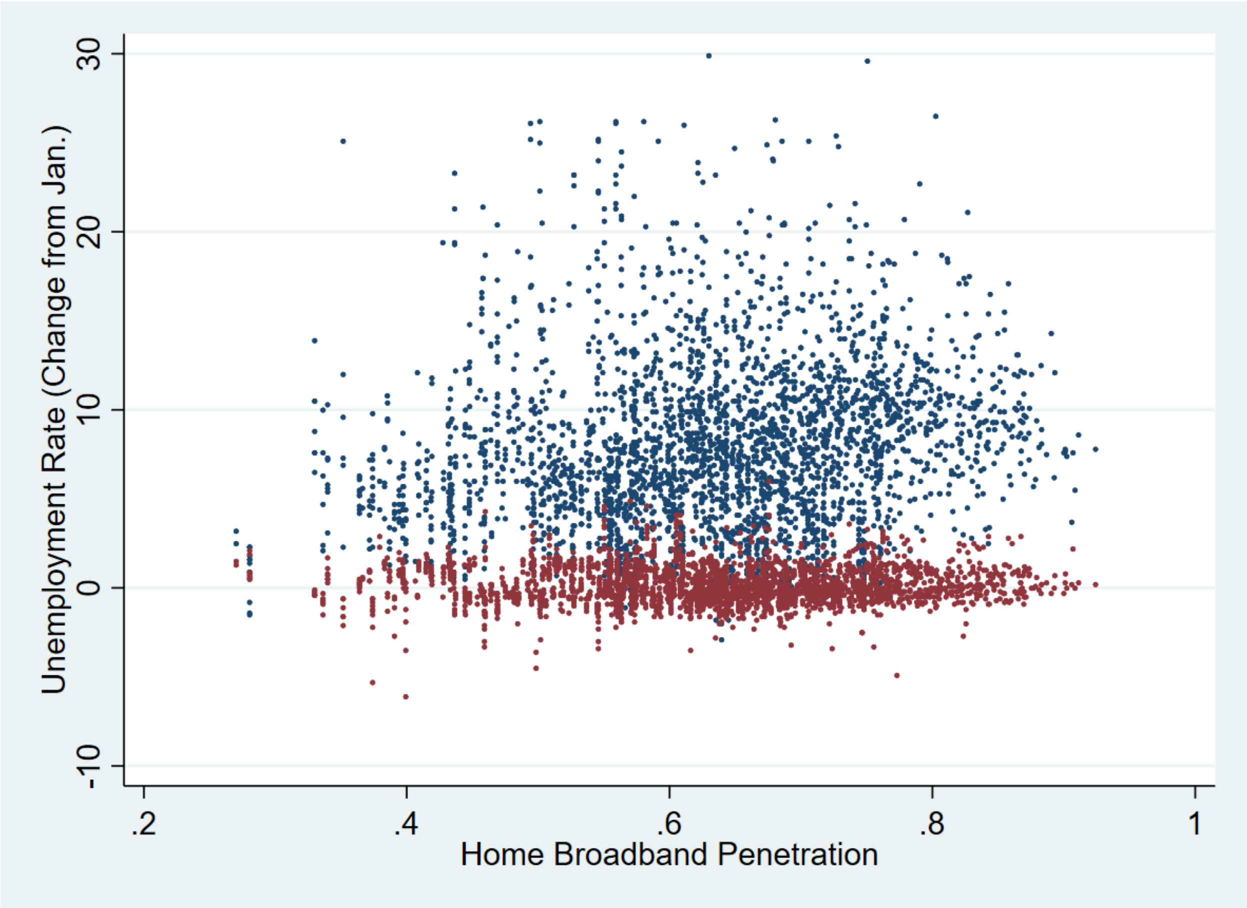
Appendix

Figure A1: Unemployment Rate: Change from January



Scatterplot of change in the Unemployment Rate from Jan. 2020 in March (red dots) and April (blue dots) of 2020 versus Home Broadband Penetration (in 2018).

Table A1: County-level Characteristics Variable: Non-Missing versus Missing Residential Mobility Data

	Non-missing Residential		Missing Residential	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Home Broadband Penetration	.6841951	.1101925	.596627	.0966424
Household Income	88431.33	23022.54	74927.04	13539.78
Proportion Blue-Collar	.1485259	.0360948	.1652164	.0277528
Proportion Attended College	.4577025	.0787088	.4186565	.0650831
Proportion Black	.0726141	.1011774	.0639446	.1169538
Proportion Asian	.022809	.0407433	.0073062	.0126284
Proportion Metropolitan	.6152906	.4865464	.1452379	.3523515
Average Transit Time to Work (Hours)	.1517782	.0502076	.1267201	.0343006
Proportion Take Public Transit to Work	.0070893	.0223579	.001911	.0057733
Proportion 18 and Above	.7886647	.0294579	.7849764	.0282447
Proportion 65 and Above	.1982816	.0424149	.2141352	.0322688
Number of Observations	**1,254**		**1,859**	

Table A2: Description of Variables

Variable	Description
Home Broadband Penetration	Whether the respondent or member of their household subscribed are subscribed to the internet using broadband (high speed) internet services such as cable, fiber optic or DSL service. Population weighted proportion of full sample.
Household Income	Total money income of all household members aged 15 or above in 2017. In thousands of dollars. Weighted average of full sample.
Proportion Blue-collar	Taken from occupation coding scheme based on Census Bureau's 2010 occupation classification scheme. We take blue-collar as anyone who has worked before and with occupational codes 6000 to 9800. The general categories are: 10 – 950: Management, Business, Science and Arts. 1000 – 1980: Computer and Mathematical. 2000 – 2920: Community and Social Services. 3000 – 3950: Healthcare practitioners and Technical. 4000 – 4965: Food Preparations and Serving. 5000 – 5940: Office and Administrative Support. 6000 – 6940: Farming, Fishing and Forestry. 7000 - 9750: Installation, Maintenance, Transportation and Repair. 9800 – 9830: Military Specific. 9920: Unemployment or Never Worked.
Proportion Attended College	Population weighted proportion of full sample that had at least attended some college
Proportion Black	Population weighted proportion of the full sample that identifies as Black or African American
Proportion Asian	Population weighted proportion of the sample that identifies as Asian
Proportion Metropolitan	All counties that are considered in a combined statistical area as defined by the United States Office of Management and Budget. It is a combination of metropolitan and adjacent micropolitan statistical areas across all fifty states that can demonstrate economic or social linkage as evidenced by commuting patterns. There are 172 Combined Statistical Areas in the United States. It is thus the largest definition of what counts as Metropolitan areas in the United States.
Average Transit Time to Work (Hours)	Population weighted average time it takes for the respondent in the sample to commute to work. In number of hours.
Proportion Take Public Transit to Work	Population weighted proportion of the respondent in the sample that takes public transit of any kind to work.
Proportion 18 and Above	Population weighted proportion of the sample who reported they are at least 18 years of age.
Proportion 65 and Above	Population weighted proportion of the sample who reported they are at least 65 years of age.