Social Distancing, Labor Market Outcomes, and Job Characteristics in the COVID-19 Pandemic

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Abstract

This paper investigates the role of job characteristics on an individual's decisions to self-isolate, work, and apply for unemployment insurance in the US during the COVID-19 pandemic. We use data that track millions of mobile devices and their daily movements across physical locations to measure whether the mobile devices leave their homes, or part-time or full-time at work that day, and we also collect data on weekly unemployment insurance claims. We find that the presence of jobs with high work-from-home capacity in a region increases the ability of people to self-isolate and decreases their unemployment risk, whereas the presence of jobs with high physical proximity decreases the incidences of self-isolation and unemployment and increases the incidence of work during the pandemic. These heterogeneous responses based on local job characteristics persist even conditional on a broad set of demographic and socioeconomic variables.

Keywords: work-from-home, physical proximity, social distancing, employment, COVID-19

JEL Classification: J22, E24, R12, J10

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1 Introduction

The discussions about the impacts of the COVID-19 pandemic and the public policies implemented after the outbreak have frequently focused on some forms of inequality. The pandemic was described in the early days, at least by some commentators, as a "Great Leveler" (Scheidel, 2018). Rich or poor around the globe, the virus can strike anyone, and everyone's life was plunged into turmoil and insecurity after the resultant mitigation policies such as lockdowns. As the pandemic progresses and the health and economic hardships become more evident, however, a fast growing literature has emerged on the distributional impacts of the pandemic across different demographic and socioeconomic groups. Early evidence shows that demographic and socioeconomic characteristics are associated with COVID-19 testing and infections (e.g., Borjas, 2020; Almagro and Orane-Hutchinson, 2020), social distancing (e.g., Allcott et al., 2020; Chiou and Tucker, 2020) and employment losses (e.g., Cajner et al., 2020; Cho and Winters, 2020). Unlike the previous studies, this paper highlights the role of job characteristics on individuals' responses to the virus and government policy directives and examines the differential impacts of the pandemic on self-isolation and employment outcomes depending on job characteristics.

To investigate this question, we construct each job's capacity to work from home and its physical proximity in the workplace by using information on attributes at detailed occupational level from the Department of Labor's most recent version of Occupational Information Network (O*NET) , following the recent work by Dingel and Neiman (2020) and Mongey et al. (2020). We combine occupation-level job characteristics with individual data from the 2014-2018 5-year American Community Survey (ACS) to construct county-level average job characteristics. We show that there exist substantial variations in the average job characteristics, measured by work-from-home capacity and physical proximity, across US counties.

We also use data that track millions of mobile devices and their daily movements across physical locations provided by Safegraph. This data allow us to observe when people stay at home, and when they are at work part-time or full-time each day, which we use to measure social distancing and employment outcomes during the pandemic. We supplement the Safegraph data on day-to-day work behavior change with weekly unemployment insurance claims data to provide a more complete picture on how the crisis leads to employment losses. We combine these social distancing and labor market outcome variables with data on regional job characteristics and other demographic and socioeconomic characteristics.

We find heterogeneous responses to the COVID-19 pandemic depending on local job characteristics across US counties and states. We show that percent of devices that stayed at home increased, percent of devices full-time at work and percent of devices part-time at work decreased, and unemployment rate rose significantly after the effects of the pandemic became clear to most people in the US and subsequent government directives. In addition, staying at home became strongly and positively correlated with work-from-home capacity, and unemployment became significantly negatively correlated with work-from-home capacity by region after the outbreak. We also find that people in counties with high physical proximity jobs became less likely to stay at home, more likely to be at work full-time or part-time, and less likely to be unemployed during the pandemic.[1] These heterogeneous responses to the pandemic persist even conditional on regional demographic and socioeconomic characteristics, such as gender, race, age, education, income, high-speed Internet access, and political beliefs. We also show that the differential responses depending on local job characteristics vary across regions.

This paper contributes to an emerging and rapidly growing literature that tries to understand the economic consequences of the COVID-19 pandemic and government interventions. Brodeur et al. (2020) provide an extensive literature review on this literature. The existing

[1] Existing studies have considered both responses to perceived risk of the coronavirus (e.g., the first case and the first death in a local region) and responses to policy directives (e.g., regional lockdown policies). These actions are shown to be interrelated (Brzezinski et al., 2020), thus we do not try to separately identify the responses to the perceived risk of the virus or the responses to policy directives after the COVID-19 outbreak. In fact, our results are quite robust when we compare behavior changes before and after various incidents signifying the pandemic, including the declaration of national emergency, state shelter-in-home directives, the first case and the first death in the state.

literature has also focused on analyzing to what extent demographic and socioeconomic factors matter in shaping people's responses to COVID-19. For example, social distancing in the wake of the pandemic is found to be associated with education and income (Brzezinski et al., 2020), partisan differences (Allcott et al., 2020), high-speed Internet access (Chiou and Tucker, 2020), among others. Employment outcomes during the pandemic are found to be associated with pre-pandemic wage level (Cajner et al., 2020), age, education and family income (Cho and Winters, 2020), and ethnicity (Platt and Warwick, 2020). By contrast, we focus on the role of job characteristics, instead of worker and family characteristics, in shaping individuals' responses during the pandemic. Dingel and Neiman (2020) first classify the capacity to work from home for all occupations, merge it with occupational employment counts, and ask the important question of how many jobs can be performed at home. Leibovici et al. (2020) instead classify occupations by their contact intensity. Mongey et al. (2020) show that workers in low-work-from-home or high-physical proximity jobs are more economically vulnerable and metropolitan statistical areas (MSAs) with more pre-pandemic employment in work-from-home jobs experience more increase in the incidence of staying at home. Our paper complements their work by exploiting variations in job characteristics across counties that cover the entire US and examine the influence of job characteristics before and after the outbreak of COVID-19 on the incidence of staying at home, as well as the incidences of full-time, part-time work, and unemployment insurance claims conditional on other demographic and socioeconomic variables. In addition, we investigate how the heterogeneous responses by local job characteristics vary across different regions.

The rest of this paper is organized as follows. Section 2 describes the data, highlighting some key data patterns that inform the subsequent analysis. Section 3 presents our empirical results on the heterogeneous responses in terms of social distancing and various employment outcomes by job characteristics. Section 4 provides the conclusion.

2 Data and Descriptive Statistics

In this section, we introduce our data sources, summarize the construction and measurement of our key variables, and describe data patterns of social distancing, work behavior, and unemployment insurance claims in the US before and after the COVID-19 outbreak.

2.1 Data on COVID-19

Data on COVID-19 cases and deaths at the county level are collected from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.[2] We collect data on the number of positive cases and number of deaths for daily cumulative counts and day-to-day increases. We recognize that the reported numbers of positive cases and deaths are imperfect measures of actual virus spread, especially in the early days of the outbreak due to unavailability of testing. However, the reported cases are likely to be correlated with the actual number of cases, and human behaviors may respond to the reported number of cases itself. In the first two columns of Table 1, we present the dates when the first positive case and the first death were reported in each state. On January 21, the first confirmed positive case was reported in the state of Washington, and all states had positive cases by mid-March.

To better contain and combat COVID-19, national emergency was declared on March 13. We collect data from the National Governors' Association on state government measures implemented to combat the COVID-19 spread.[3] We present data on when each state issued an order for shelter-in-place (or stay-at-home) in the third column of Table 1. Statewide shelter-in-place order was first issued in California on March 19. The shelter-in-place order called for all citizens to stay at home. Other states followed suit and by the first week of April, all states had implemented similar stay-at-home orders. School and business closure were also implemented in all states. The business closure order required all non-essential businesses to close down. Although states vary in their definitions for essential businesses,

[2] Available at https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data.
[3] The underlying data can be found at https://www.nga.org/coronavirus/#states.

grocery stores and medical emergency services are typical essential businesses.

2.2 Data on Job Characteristics

Individuals with different jobs vary substantially in their exposure to social distancing policies and labor market shocks during the COVID-19 pandemic. We construct measures of each job's capacity to work from home and its physical proximity in the workplace by using information on attributes at detailed occupational level, following the recent work by Dingel and Neiman (2020) and Mongey et al. (2020). Specifically, we construct occupational-level indexes for work-from-home capacity and physical proximity using data from the Department of Labor's most recent version of Occupational Information Network (O*NET), following Mongey, Pilossoph and Weinberg (2020).[4] To construct the index for work-from-home capacity, 17 measures of occupation attributes in the O*NET are used, including eight elements from the work activities module and nine elements from the work contexts module (Dingel and Neiman, 2020).[5] The index for physical proximity is derived from the work context element "physical proximity" in O*NET.[6]

For each occupation i in O*NET and each attribute k selected to measure work-from-home capacity, a value v_{ik} between 1 and 5 is reported in the O*NET data based on the average response of workers to an underlying survey question, with 5 indicating low possibility to work-from-home in the workplace.[7] Occupations are defined at the SOC level in O*NET,

[4]The authors provide replication codes at https://github.com/simonmongey/Mongey_Pilossoph_Weinberg. We successfully replicate the indexes by following their steps introduced in the paper.

[5]The eight elements from the work activities module include performing general physical activities (4.C.1.a.2.h), handling and moving objects (4.A.3.a.2), controlling machines and processes (4.A.3.a.3), operating vehicles, mechanized devices, or equipment (4.A.3.a.4), repairing and maintaining mechanical equipment (4.A.3.b.4), and repairing and maintaining electronic equipment (4.A.3.b.5), performing for or working directly with the public (4.A.4.a.8), and inspecting equipment, structures, or material (4.A.1.b.2). The nine elements from the work contexts module are electronic mail use (4.C.1.a.2.h), deal with physically aggressive people (4.C.1.d.3), outdoors, exposed to weather (4.C.2.a.1.c), outdoors, under cover (4.C.2.a.1.d), exposed to minor burns, cuts, bites, or stings (4.C.2.c.1.f), exposed to disease or infections (4.C.2.c.1.b), spend time walking and running (4.C.2.d.1.d), wear common protective or safety equipment such as safety shoes, glasses, gloves, hearing protection, hard hats, or life jackets (4.C.2.e.1.d), and wear specialized protective or safety equipment such as breathing apparatus, safety harness, full protection suits, or radiation protection (4.C.2.e.1.e). Codes in parentheses are the corresponding questions listed in O*NET.

[6]Question code for physical proximity in O*NET is 4.C.2.a.3.

[7]We reverse the original scale of electronic mail use to make it consistent with other attributes.

which is finer than the Census OCC occupation codes. The Census Bureau provides a crosswalk that matches SOC to OCC occupations.[8] For each OCC occupation j, we take the employment-weighted average of v_{ik} for all SOC occupation i covered by occupation j and denote it as $\bar{v}_{jk}$, where the SOC level employment is available from the Occupational Employment Statistics (OES) from Bureau of Labor Statistics. Following Mongey et al. (2020), we convert these averages into binary variables, such that $v^*_{jk} = 1$ if $\bar{v}_{jk} < 3.5$. Then we construct a work-from-home measure, WFH_j, for each occupation j by taking the average of v^*_{jk} across all elements k included to measure work-from-home capacity. Similarly, to construct an index for each OCC occupation's physical proximity, we start with the work context element "physical proximity" from the O*NET that takes a value between 1 and 5 at the SOC level, with higher number indicating higher physical proximity in the workplace. We use the OES employment to compute an employment-weighted mean for all OCC occupations and use it as our physical proximity measure, HPP_j. We rescale both indices to lie between 0 and 1 by subtracting the minimum values and diving by the differences between the maximum and the minimum values.

We examine the relationships between job characteristics, measured by WFH and HPP indices, and worker characteristics in Tables 2 and 3. Table 2 reports top and bottom 20 occupations in terms of their capacity to work-from-home. The occupations with the highest WFH index include managers, teachers, computer scientists and lawyers, whereas occupations such as power-line installers, firefighters, and machine operators are difficult to work-from-home. Next to the WFH index in Table 2, we present the characteristics of workers in each of these occupations, including percentages of female workers, black workers, workers with no college degree, workers below age 50, and immigrant workers. Worker characteristics within each occupation are based on data from the 2014–2018 5-year pooled American Community Survey (ACS). We observe large variations in worker characteristics for occupations with similar WFH index. For example, childcare workers and lawyers have the

[8] The crosswalk from census is available at: https://www2.census.gov/programssurveys/demo/guidance/industry-occupation/2010-occ-codes-with-crosswalk-from-2002-2011.xls.

same WFH index, but 83.9 percent of childcare workers have no college degree as compared to only 1.8 percent of lawyers without college degree. When we compare the employment-weighted average characteristics for the top and bottom work-from-home occupations, we find that high work-from-home occupations have much higher percentage of females workers (59.8 percent versus 10.6 percent). In addition, black, non-college, younger and immigrant workers are more likely to work in occupations that are most difficult to work from home. Table 3 presents top and bottom 20 occupations in physical proximity in the workplace. The occupations with the highest HPP index include medical professionals, flight attendants and hair dressers. In contrast, it is much easier for logging workers, writers and computer scientists to keep physical distance at work. On average, workers in occupations with high HPP index are more likely to be female, black, non-college educated, and at younger age.

We combine occupation-level job characteristics with individual data from the 2014–2018 5-year ACS to construct county-level average occupation characteristics. The large sample size of the ACS allows us to explore the regional variations in occupation structure. The ACS provides information on each worker's occupation at OCC level, and we assign the corresponding WFH and HPP indices to each individual based on their occupation. Public Use Microdata Area (PUMA) is the smallest geography available in the ACS. They are designed to have a population of roughly 100,000 or more people. The WFH and HPP indices of each PUMA are weighted averages over individual indices within the PUMA, where the personal weights are provided by the ACS. Then, we use the crosswalk provided by Missouri Census Data Center to map the variables at PUMA level to county level.[9] The crosswalk uses population at PUMA and county levels to construct weights. If a county is fully contained in a PUMA, it has the same variables as the PUMA. If a county is divided by several PUMAs or contains several PUMAs, the variables are computed as the weighted average of the corresponding variables over the relevant PUMAs using the weights based on population.

[9]The crosswalk is available at http://mcdc.missouri.edu/data/corrlst/uscntypuma12.csv.

Figure 1a shows the variations in the WFH index across US counties. The darker color corresponds to higher capacity to work-from-home for a typical worker in the county. Regional differences in the WFH index can be largely accounted for by occupation structure. Counties with large employment shares in high-end service and high-tech jobs usually have higher WFH index. Large cities, such as New York and Washington DC, along with counties near these cities usually score high in the WFH index. Moving from the east coast to the west coast, several counties also stand out for their high scores in the WFH index because most of them have large shares of workers in high-tech and related consulting jobs. In contrast, many counties in Michigan, Ohio, and Indiana have high concentration of manufacturing jobs with low WFH scores, such as those in wood, paper and plastic products, transportation equipment, and pharmaceutical products industries. Similarly, Figure 1b shows the variations in the HPP index, with darker color representing higher physical proximity in the workplace. The HPP index largely reflects the level of direct and close interaction with people in each occupation. As shown in Table 3, healthcare professionals work in environments with high physical proximity. It is not surprising that counties with high employment share of healthcare jobs have high HPP index. Counties with large shares of workers in retail sales and food and accommodation services also tend to have higher HPP index. We observe considerable overlap between counties with high WFH index and those with low HPP index as these counties tend to have clusters of high-end service and high-tech occupations.

2.3 Data on Social Distancing and Labor Market Outcomes

We use high-frequency data provided by SafeGraph to study social distancing and work behavior across the US during the pandemic. SafeGraph collects highly disaggregated daily information on individual travel in the United States from a panel of over 20 million smartphone devices. Each user of these devices is anonymous but has given permission for their location to be tracked by various mobile apps. After the outbreak, SafeGraph made two "COVID-19 response datasets" freely available to the research community. In the "weekly patterns" dataset, the locations of the devices are matched to Points of Interests (primarily retail stores and other businesses) with exact physical location at hourly frequency. In the second dataset, named "social distancing metrics," individual device's foot traffic information is available at daily frequency.[10]

One social distancing metric provided by SafeGraph is the number of cellphones in the sample that completely stay at home, as measured by cellphones that do not leave a small area at nighttime.[11] The devices are then aggregated by home census block group. In addition to the number of devices that stay at home the entire day in each census block group, two work behavior variables of devices are available in the dataset. A device is counted as "full time at work" if it spends greater than 6 hours at a location other than its home location during the period of 8am-6pm in local time and as "part time at work" if it spends one period of between 3 and 6 hours at one location other than its home location during the period of 8am-6pm in local time. Daily data on social distancing metrics is available going back to January 1, 2020. The dataset contains information across more than 200,000 census block groups with at least 5 devices.[12]

We aggregate measures on social distancing and work behavior up from the census block group level to the county level. Specifically, we construct, on a daily basis, the following three variables: (1) the percentage of devices that spent all day at home, which is obtained by dividing the number of such devices in a county by the total number of devices observed in the county; (2) the percentage of full-time at work, which is computed by dividing the number of devices counted as "full time at work" by the total number of devices in a county; (3) the percentage of part-time at work, which is calculated by dividing the number of devices

[10] More details on the SafeGraph COVID-19 response datasets can be found at https://docs.safegraph.com/docs.

[11] SafeGraph describes its definition of cellphone home as follows: "The data was generated using a panel of GPS pings from anonymous mobile devices. We determine the common nighttime location of each mobile device over a 6 week period to a Geohash-7 granularity ($\sim$153m $\times$ $\sim$153m). For ease of reference, we call this common nighttime location, the device's 'home.'"

[12] As discussed by Brzezinski et al. (2020), geographic and demographic biases of the sample are limited. SafeGraph guarantees individual privacy by reporting mobility patterns only at the aggregate census block group level.

counted as "part time at work" by the total number of devices in a county.

We supplement the Safegraph data on day-to-day work behavior change with weekly unemployment insurance (UI) claims data to provide a more complete picture on how the pandemic leads to employment losses. The UI program is a joint state-federal program that provides cash benefits to eligible workers. Each state administers a separate program, but all states follow the same guidelines established by federal law. The UI program records represent about 95 percent of all jobs in the country. Data on covered employment by the UI program are collected from employers. The determinants on eligibility of UI benefits vary across states but there are two common requirements in all states. First, workers are unemployed through no fault of their own. Second, workers need to meet the work and wage requirements. People who file their first claims in a year are counted as number of first claims, and they are required to file their weekly claims to prove their eligibility, which are counted as number of continued claims. The number of continued claims reflects the total number of unemployed people in the UI program in a week. The UI claims data are collected at state level and available from the Department of Labor.[13] In our analysis, we calculate weekly (insured) unemployment rate by state as the ratio between the number of continued claims over the covered employment in the state.

Figure 2 depicts the trends in social distancing and labor market outcomes in the US during the pandemic. We plot the percentage of devices that stayed home all day (Figure 2a), the percentage of devices full-time at work (Figure 2b), the percentage of devices part-time at work (Figure 2c), and the percentage of unemployment (Figure 2d) from the beginning of January 2020 until the end of April, respectively, alongside the dates of first case (January 21) and first death (Feburary 29) in the US, and the declaration of national emergency (March 13). In each panel of Figure 2a-2c, we plot the daily median value of the variable across counties (the dashed line), as well as the 7-day moving average of the daily median (the solid line). Not surprisingly, the daily data series exhibit striking weekly patterns, with

[13] https://oui.doleta.gov/unemploy/DataDashboard.asp

the proportion of devices at home surging and the proportions of devices full-time or part-time at work dropping on weekends. According to Figure 2a, the percentage of devices that stayed at home seems to be stationary until the first week of March, when it started to increase substantially. The upward trend continued throughout March, and the nation-wide state of emergency declaration appeared to have led to an acceleration of the increase. After the first week of April, the proportion of devices at home started to decline but it remained much higher than its pre-crisis level by the end of April. According to Figures 2b and 2c, the percentages of devices full-time at work and part-time at work were relatively stable before the first week of March and then dropped significantly in March and stayed at much lower level in April. In addition, the average unemployment rate was low and stable until the third week of March and then increased drastically in April.

The demographic and socioeconomic characteristics of the population and workforce vary substantially across states, and the timing of the COVID-19 outbreak and lockdown policies also differ significantly across states (Table 1). Therefore, individual responses in terms of social distancing and work behavior likewise vary substantially across geographic locations. In Figure 2, each gray dot represents a daily observation for a state. The daily large dispersion indicates considerable variations in these social distancing and work behavior variables. In Appendix Figures A1-A4, we further plot the county-level percentages of devices that stayed at home, full-time at work and part-time at work on the second Wednesday of each month and the state-level unemployment rates in the second week of each month in the first four months of 2020, respectively. We observe substantial variations on a daily basis in percentages of devices at home, full-time at work and part-time at work across counties before the crisis, as well as in the magnitude of their changes during the pandemic. Although unemployment rate had relatively small variations across states before the virus outbreak, its increase varied substantially across states in April.

We also use the ACS data to construct county-level demographic composition and other socioeconomic variables. Table 4 presents summary statistics of the key variables. We have data on 3,142 counties each day from January 1 to April 30, 2020. On average, there were 65 reported cases of COVID-19 at the county level in our dataset, but there exist enormous variations across counties. The average county has a WFH index of 0.74 and a HPP index of 0.56. On average throughout our sample period, 27.8 percent of devices stayed at home all day, 5.4 percent of devices spent more than 6 hours at a location other than their home location between 8am-6pm each day, 9.1 percent of devices spent between 3 and 6 hours at a location other than home during working hours, and 3.3 percent of the covered employment claimed for unemployment insurance. The median household income across counties was around $52,000, and the average population density was 270 persons per square mile. On average, 89 percent of individuals were covered by either public or private health insurance, 59 percent of households reported access to high-speed Internet, and 63 percent voted for the Republican party in the 2016 Presidential election.[14]

3 Empirical Analysis

In this section, we first present simple statistical evidence on how changes in social distancing and other labor market outcomes across US counties are associated with pre-pandemic features of local jobs. Then we turn to more rigorous econometric specifications, which exploit the exact timing of policy directives or virus spread and examine how the responses to stay home, work, and apply for unemployment insurance vary with local job characteristics conditional on other regional socioeconomic and demographic characteristics.

3.1 Behavior Changes by Job Characteristics

We begin by presenting some raw evidence on how behavior changes across counties in terms of social distancing, work, and unemployment insurance claims are associated with local job characteristics. Figure 3 compares behavior changes in counties with above median and

[14]County-level 2016 Presidential Election Results are taken from the MIT Election Data and Science Lab. The county-level variables are averages across all counties without using county population as weight.

below median WFH index before and after the national emergency declaration on March 13. Figure 3a shows that prior to two weeks before the national emergency declaration, counties with above median WFH index had similar proportions of devices that stayed at home all day as counties with below median WFH index. However, after the end of February, people living in counties with high WFH index were substantially more likely to stay at their homes than people living in counties with low WFH index. It is important to note that counties with high WFH index have reasonably broad coverage across the country and are not concentrated in one region, as shown in Figure 1a. Figure 3b shows that slightly lower percentages of devices from counties with high WFH index were full-time at work than those from counties with low WFH index, before and after the national emergency declaration. The percent of devices full-time at work declined significantly after the national emergency declaration for all counties, but there seems no significant difference in the pattern of change for counties with above and below median WFH index. Figure 3c shows that counties with high WFH index had slightly lower percent of devices part-time at work than counties with low WFH index before the national emergency declaration, but after mid-March, this difference became much larger. Figure 3d shows that states with below median WFH index and those with above median WFH index had the same percentages of unemployment insurance claims before the national emergency declaration. The unemployment rate increased drastically after the end of March, and counties with high WFH index appears to have relatively lower percentage of unemployment insurance claims.

Similarly, Figure 4 compares behavior changes in counties with above median and below median HPP index before and after the national emergency declaration. Figure 4a shows that prior to the national emergency declaration, devices in counties with high HPP index were slightly more likely to stay at home than those in counties with low HPP index; whereas after the national emergency declaration, devices in counties with high HPP index were much less likely to stay at home. Figures 4b and 4c show that devices in counties with high HPP index were less likely to be full-time or part-time at work before the national emergency but they became more likely to be part-time at work after the national declaration than those in counties with low HPP index. Figure 4d shows that slightly higher percentage of people applied for unemployment insurance in counties with below median HPP index, but the difference in unemployment rate disappeared after the end of March. Note that counties with high HPP index also spread across the country and are not concentrated in one region.

The similarities in Figures 3 and 4 reflect the fact that having a high WFH index in a county and a low HPP index is correlated. Although the correlation between the WFH index and the HPP index is relatively low at -0.12 across occupations, the same correlation is much higher across counties at -0.55 because of the regional clustering of occupations. In the subsequent analysis, we will examine the extent to which the regional differences in self-isolation, work and unemployment behavior that can be attributed to disparities in work-from-home capacity and physical proximity of local jobs individually and jointly.

In Figures 3 and 4, we compare behavior changes before and after the national emergency declaration. Previous studies have shown that individuals engaged in social distancing even in the absence of state directives, once the virus started spreading in their area (Brzezinski et al. 2020; Engle, Stromme and Zhou, 2020). Figures 2a, 3a and 4a also confirm that people started to practice social distancing about two weeks before the national emergency declaration on March 13. We do not try to separately identify the responses to the perceived risk of the virus or the responses to policy directives after the COVID-19 outbreak. To investigate whether behavior changes respond differently to state directives or the virus spread, we make the similar plots in Figures A5 and A6 as those in Figures 3 and 4, but compare behavior changes before and after the first case in the state. As states vary in the date when the first COVID-19 case was reported, we set the first case date as zero and compare the changes before and after it. We observe similar patterns of changes for counties with above and below median WFH or HPP index as those in Figures 3 and 4. We further compare behavior changes before and after the first death in the state (Figures A7 and A8), as well as before and after the shelter-in-place order in the state (Figures A9 and A10), the overall patterns are all similar.

3.2 Empirical Specification and Estimation Results

Although the comparisons in Figures 3 and 4 are useful, they do not control for differences in demographic and socioeconomic characteristics across counties other than local job characteristics. A more informative documentation of how behavior changes are associated with local job characteristics would show behavior changes in counties with different local job characteristics, holding demographic and other socioeconomic characteristics in the region fixed. Thus, we consider the following econometric specification.

$$\begin{aligned} Y_{cst} = \beta_0 + \beta_1 \times EVENT_{st} + \beta_2 JOB_{cs} \times EVENT_{st} + \beta_3 JOB_{cs} \\ + \boldsymbol{X}_{cst}\boldsymbol{\Gamma} + \rho_s + \delta_t + \epsilon_{cst}, \end{aligned} \tag{1}$$

where Y_{cst} denotes outcome variables, including percent of devices that stayed at home, percent of devices full-time at work, percent of devices part-time at work, and percent of workforce that filed for unemployment insurance, in county c of state s on date t. $EVENT_{st}$ is a dummy variable that captures the precise timing of events in state s in our data. In our baseline specification, we consider the declaration of national emergency, but we also consider three other relevant events at state level: the occurrence of first COVID-19 case, the occurrence of first COVID-19 death in the state, and the state shelter-in-place directive, with dates after the event having $EVENT_{st} = 1$ and $EVENT_{st} = 0$ otherwise. JOB_{cs} captures the local job characteristics in county c of state s, and it is either measured by WFH_{cs} or HPP_{cs}, where WFH_{cs} and HPP_{cs} are dummy variables that equal to 1 if the county-specific WFH and HPP indices are above the median and equal to 0 otherwise. X_{cst} is a vector of county demographic and socioeconomic characteristics, as well as county-level variables that changed over time; ρ_s is a vector of state fixed effects intended to capture baseline regional differences in individual behaviors; δ_t is a vector of weekday fixed effects to capture day-to-day fluctuations within each week in the outcome variables; and ϵ_{cst} is an idiosyncratic shock.[15] The coefficient β_1 captures the level effect of the pandemic on outcomes. The coefficient on the interaction term, β_2 is the coefficient of our main interest, which captures the relative effect of the occurrence of the event for counties with high WFH or HPP indices.

Table 5 presents results on how the effects of the COVID-19 pandemic on social distancing and labor market outcomes depend on local jobs' WFH capacity. We use the national emergency declaration as an indicator for the outbreak. In all specifications we control for state fixed effects, thus we are only looking at variation in local job characteristic on WFH within a state rather than variation across states. Columns 1, 3, 5, 7 of Table 5 present how local WFH affects percent of devices that stayed at home, percent of devices full-time at work, percent of device part-time at work, and unemployment rate, respectively, before and after the national emergency declaration without controlling for regional demographic and other socioeconomic characteristics. We find that percent of devices that stayed at home increased, percent of devices full-time at work and percent of devices part-time at work decreased, and unemployment rate rose significantly after the national emergency declaration for all counties. Before the pandemic, devices located in counties with high WFH capacity were less likely to stay at home. However, staying at home became strongly and positively correlated with WFH capacity after the outbreak. In addition, part-time work and unemployment became significantly negatively correlated with WFH capacity by region after the national emergency declaration.

Other factors have been used to explain regional differences in social distancing and labor market outcomes. In columns 2, 4, 6 and 8 of Table 5, we include additional controls for regional demographic and other socioeconomic variables. In particular, we include local demographic composition by gender, race, age, education and immigration status as controls. We also have local average household income, population density, health insurance coverage, high speed internet coverage (Chiou and Tucker, 2020) and share of votes for the Republican

[15] As our data on unemployment rates are at state level and on weekly basis, we do not control for ρ_s and δ_t when Y_{cst} denotes percent of unemployment in Equation (1).

Party in the 2016 presidential election (Allcott et al. 2020; Engle, Stromme and Zhou, 2020; Painter and Qiu, 2020) as additional controls. Finally we include the daily county-level (or weekly state-level, in the unemployment regression) reported COVID-19 cases per 1000 persons. After controlling for various demographic and socioeconomic variables, we still find significantly heterogeneous responses after the national emergency declaration depending on local WFH capacity, as indicated by the coefficients on the WFH and event (national emergency declaration) interaction term. Regions with high WFH capacity increased the incidence of staying at home much more than regions with low WFH capacity. They also decreased the incidence of part-time work more and became less likely to be unemployed after the national emergency declaration. We find no difference in the incidence of full-time work after the pandemic between regions with high WFH and low WFH capacity. These results suggest that jobs with high WFH capacity have more flexibility for social distancing, and they seem to be more stable during the pandemic. Most of the estimated coefficients on the other controls variables have expected signs and are consistent with previous studies. For example, higher income and higher education are associated with less employment loss (Cajner et al., 2020; Cho and Winters, 2020), high speed internet access facilitates social distancing (Chiou and Tucker, 2020), counties with larger share of Republican votes are less likely to practice social distancing (Allcott et al. 2020; Engle, Stromme and Zhou, 2020; Painter and Qiu, 2020)

Table 6 summarizes the results on how local jobs' characteristics on physical proximity (HPP) affect the behavior responses in social distancing and labor market outcomes during the pandemic. Again, we are most interested in the coefficients on the interaction term between the HPP dummy and the event. We use similar specifications as those in Table 5 without and with controls on local demographic and other socioeconomic characteristics. We find that devices in counties with high physical proximity jobs became less likely to stay at home, more likely to be at work full-time or part-time during the pandemic. These results are robust if we include regional demographic and socioeconomic characteristics. Workers in counties with high HPP were also less likely to be unemployed after the outbreak once we control for other regional characteristics. These results are driven by the fact that HPP is a characteristic of many occupations designated as essential business during the pandemic, as shown in Table 3.

In Table 7, we examine the effects of local job characteristics on WFH and HPP jointly. We find that the heterogeneous responses due to local jobs' WFH capacity in the pandemic found in Table 5 are robust even after controlling for local jobs' characteristic on HPP, except for that the effects on part-time work become statistically insignificant. Similarly, the heterogeneous responses due to local jobs' HPP found in Table 6 are also robust after controlling for WFH. Therefore, WFH and HPP are two distinctive job characteristics that affect people's behavior responses during the pandemic despite their correlations across occupations and regions. In Appendix Table A1, we compare the results when four alternative events, including the declaration of national emergency, first case in state, first death in state and state shelter-in-place directive, as indicators for the outbreak of COVID-19. We find that our results are robust.

In Tables 8 and 9, we compare the heterogeneous responses after the national emergency declaration by local job characteristics in regions with above median and below median education level, family income, high speed Internet access, and share of Republican votes. In all regressions in Tables 8 and 9, we control for other local characteristics. Table 8 shows that the positive correlation between WFH and changes in stay-at-home incidence during the pandemic is significantly stronger in regions with higher education level, higher income, more access to high-speed Internet, and fewer Republican votes. These socioeconomic characteristics of the local labor market seem to exacerbate the unequal impact of the pandemic based on local jobs' WFH capacity. The effects of WFH on changes in full-time work and part-time work are not statistically different for regions with different characteristics. Finally, the lower unemployment rate for counties with high WFH capacity are driven by counties with higher education, higher income, better high-speed Internet access, and lower share of

Republican vote. In addition, in counties with low high-speed Internet access, high local WFH capacity is associated with higher unemployment rate in the pandemic although the effect is opposite in counties with high high-speed Internet access. One explanation is that the ability to access high-speed Internet is necessary for people to work from home. In Table 9, we show that the lower stay-at-home, higher full-time and part-time work incidence for counties with high HPP are all driven by counties with higher education, higher income and better access to high-speed Internet.

4 Conclusion

This paper documents how the impacts of the COVID-19 pandemic on self-isolation, work, and unemployment across regions in the US depend on the characteristics of local jobs that are characterized by their work-from-home capacity and physical proximity. We present evidence that the presence of above median WFH jobs in a region increases the ability of people to self-isolate and decreases their unemployment risk during the pandemic. At the same time, the presence of above median HPP jobs decreases the incidences of self-isolation and unemployment and increases the incidence of work after the outbreak. We find that these heterogeneous responses based on local job characteristics persist even conditional on a broad set of demographic and socioeconomic variables such as gender, race, age, education, and income.

Our results have implications for public policy. Workers in low work-from-home jobs face both higher health risks and higher economic risks, whereas workers in jobs with high physical proximity face higher health risks but lower economic risks during the pandemic. These results provide guidance as to how public health and economic assistance policies may be targeted. They also highlight that the geographic clustering of industry and occupation may potentially exacerbate the unequal impacts of the pandemic.

Finally, our paper focuses the differential responses in social distancing and employment/unemployment based on job characteristics during the pandemic. At labor market equilibrium, these job characteristics would be associated with different wage premiums according to compensating wage differential. Disentangling the impacts of job characteristics on earnings inequality in the wake of a global pandemic like COVI-19 remains an important topic for future research.

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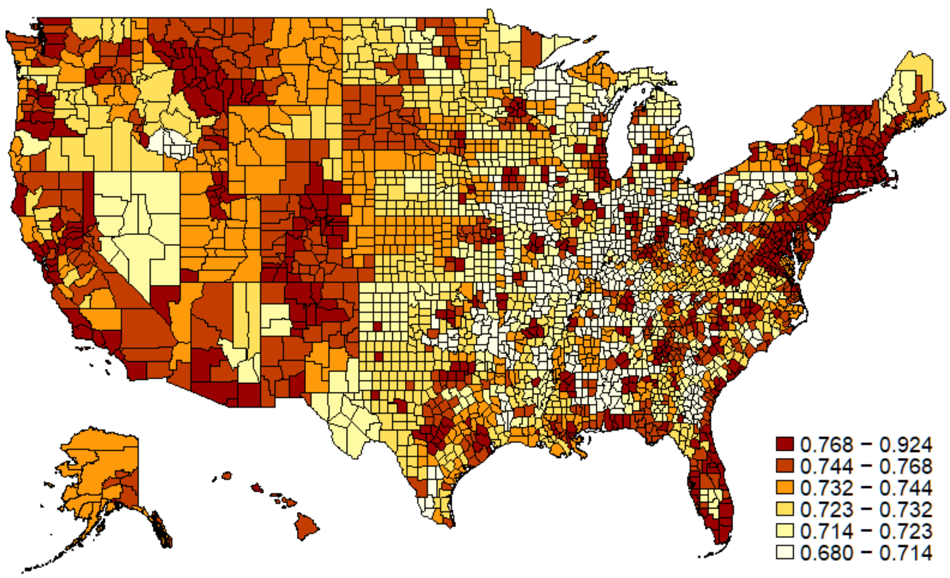
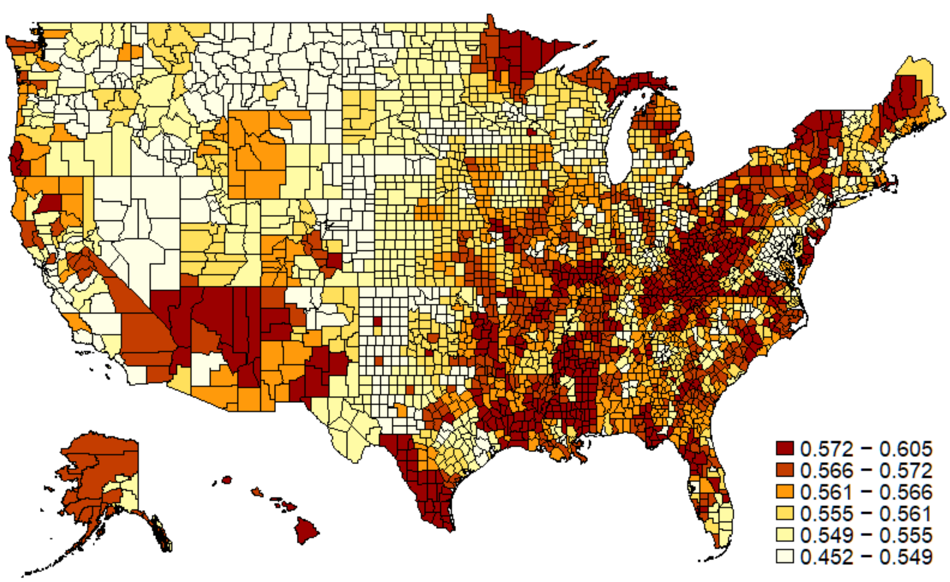
Figure 1: Job Characteristics across Counties



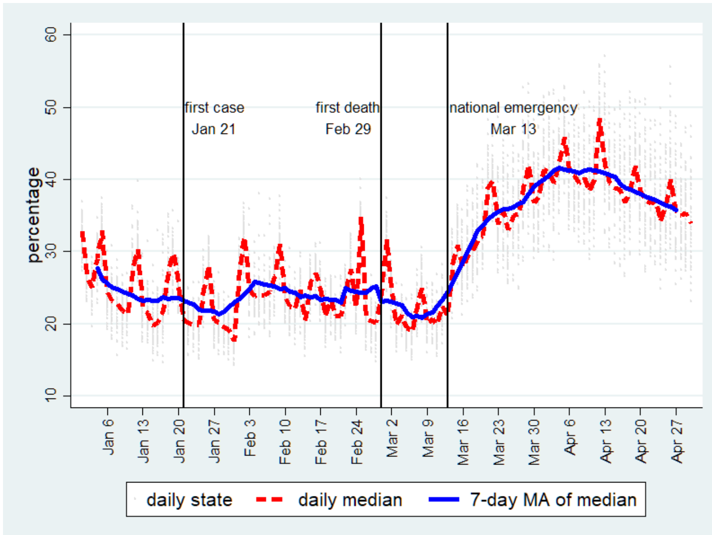
(a) Work-From-Home Index



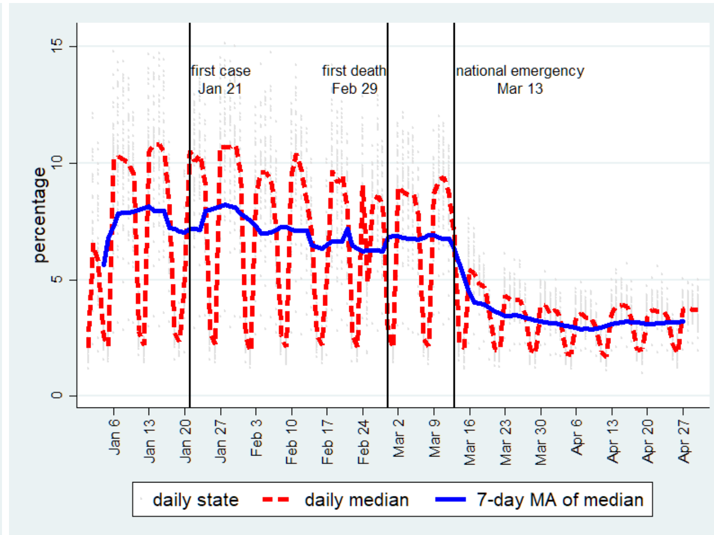
(b) High Physical Proximity Index

Notes: The WFH and HPP indices are first constructed at occupation level using occupation attributes from O*NET and employment from OES. Then the occupation-level indices are combined with individual data from the 2014–2018 5-year ACS to construct county-level average WFH and PP indices.

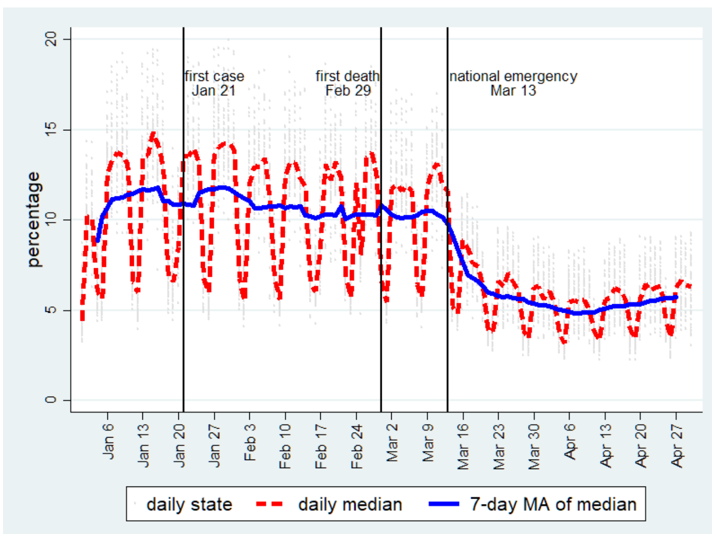
Figure 2: Changes in Social Distancing and Work Behavior, January–April 2020



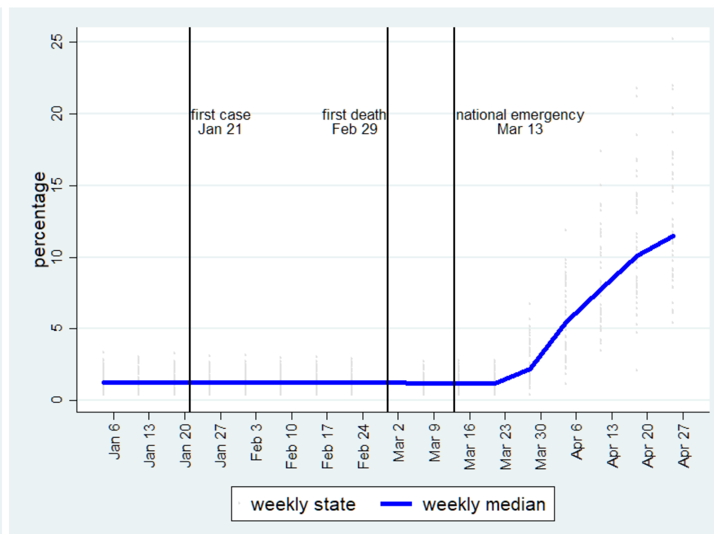
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



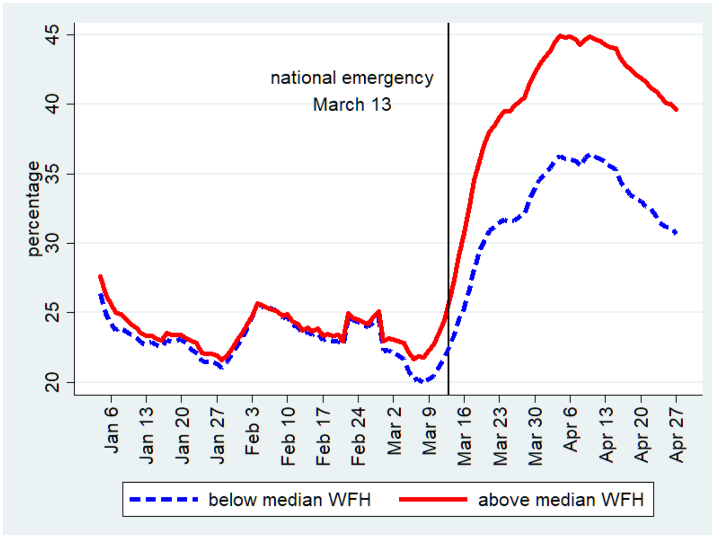
(c) Percent of Devices Part-time at Work



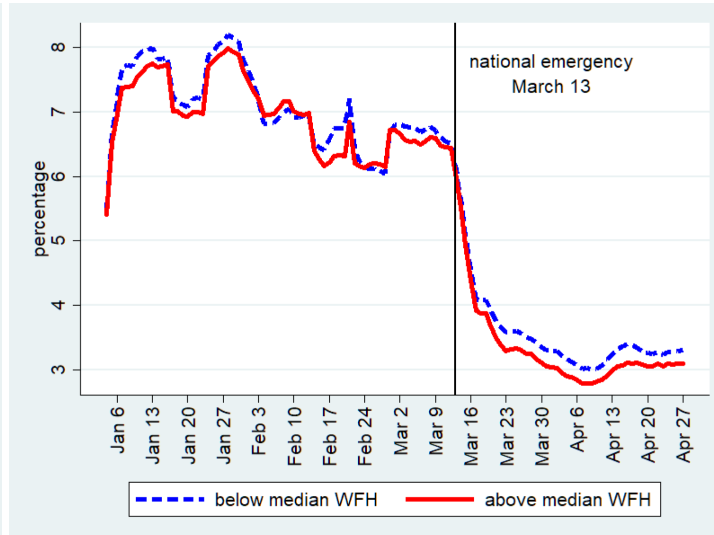
(d) Percent of unemployment

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from the Department of Labor.

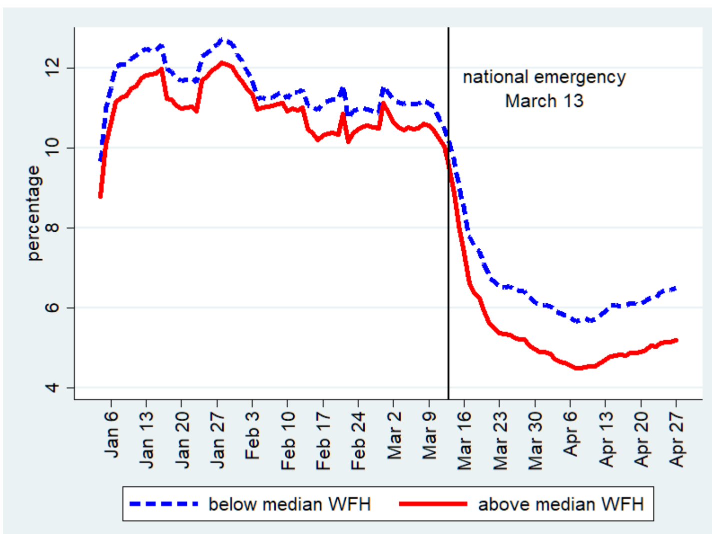
Figure 3: Behavior Changes by Local WFH Index Before and After National Emergency



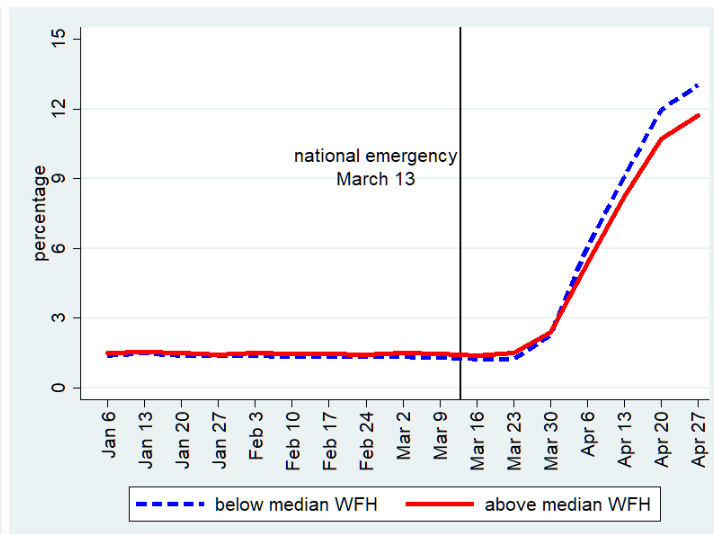
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



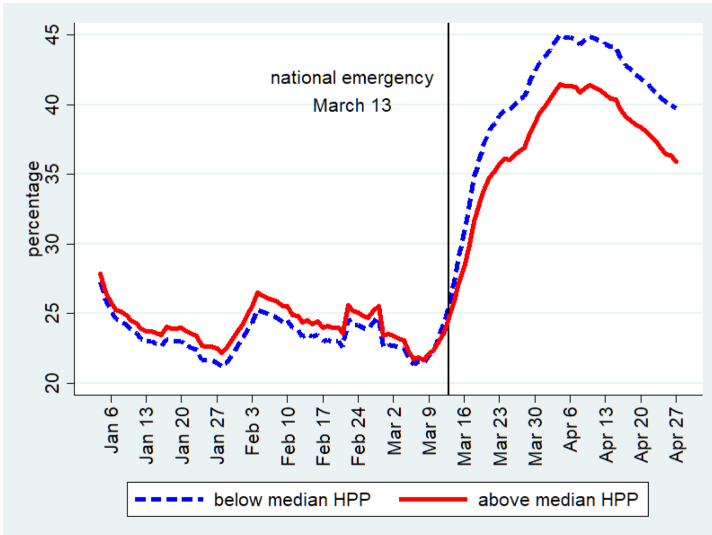
(c) Percent of Devices Part-time at Work



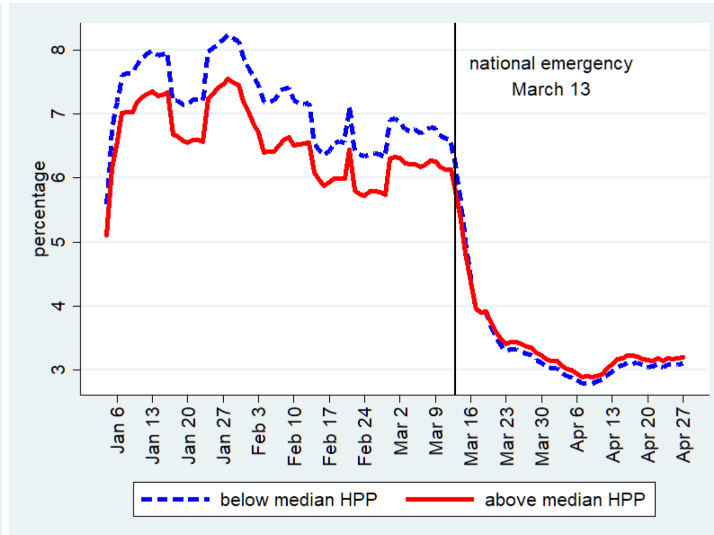
(d) Percent of Unemployment

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from the Department of Labor.

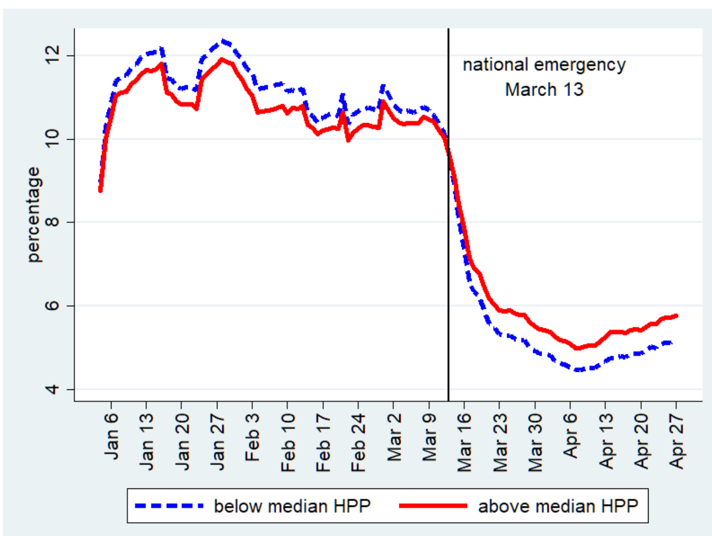
Figure 4: Behavior Changes by Local HPP Index before and After National Emergency



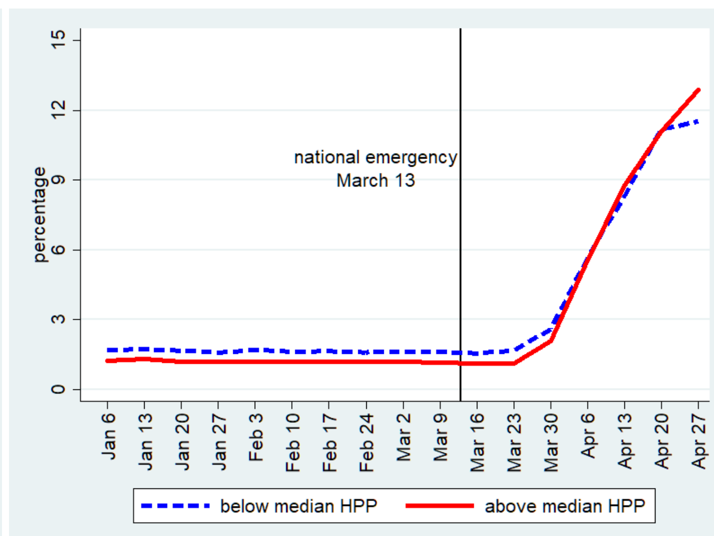
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



(c) Percent of Devices Part-time at Work



(d) Percent of Unemployment

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from the Department of Labor.

Table 1: Timeline of Covid-19 Spread and Lockdown Policies Across US States

State Name	Date of First Case	Date of First Death	Date of Shelter-in-Place	Date of School Closure	Date of Business Closure
Washington	Janurary 21	Feburary 29	March 23	March 16	March 23
Illinois	Janurary 24	March 17	March 21	March 16	March 21
California	Janurary 26	March 4	March 19	March 16	March 19
Arizona	Janurary 26	March 21	March 31	March 16	March 31
Wisconsin	Feburary 5	March 19	March 25	March 18	March 25
Oregon	Feburary 28	March 15	March 23	March 16	March 23
Massachusetts	Feburary 28	March 20	March 24	March 16	March 24
New York	March 1	March 12	March 22	March 18	March 22
Florida	March 1	March 8	Apirl 3	March 16	April 3
Rhode Island	March 1	April 3	March 28	March 16	March 28
New Hampshire	March 2	March 23	March 27	March 23	March 27
Georgia	March 2	March 12	April 3	March 18	April 3
North Carolina	March 3	March 25	March 30	March 16	March 30
Texas	March 4	March 17	April 2	March 20	April 2
New Jersey	March 4	March 10	March 21	March 18	March 22
Nevada	March 5	March 16	Apirl 1	March 16	March 20
Tennessee	March 5	March 20	March 31	March 20	March 31
Maryland	March 5	March 19	March 30	March 16	March 23
Colorado	March 5	March 13	March 26	March 23	March 26
Indiana	March 6	March 16	March 24	March 16	March 24
Oklahoma	March 6	March 19	March 24	March 17	March 24
Nebraska	March 6	March 28	April 1	Apirl 1	April 1
Minnesota	March 6	March 21	March 27	March 18	March 27
Pennsylvania	March 6	March 18	April 1	March 16	April 1
Hawaii	March 6	March 24	March 25	March 16	March 25
South Carolina	March 6	March 16	April 7	March 16	April 7
Utah	March 6	March 22	March 27	March 16	March 27
Kentucky	March 6	March 16	March 26	March 16	March 26
Virginia	March 7	March 14	March 30	March 16	March 30
Vermont	March 7	March 19	March 25	March 18	March 25
Missouri	March 7	March 18	April 6	April 6	April 6
Kansas	March 7	March 13	March 20	March 18	March 20
District of Columbia	March 7	March 20	April 1	March 16	March 25
Connecticut	March 8	March 18	March 23	March 16	March 23
Iowa	March 8	March 25	April 2	March 16	April 2
Ohio	March 9	March 20	March 23	March 16	March 23
Louisiana	March 9	March 14	March 23	March 16	April 23
Michigan	March 10	March 18	March 24	March 16	March 24
South Dakota	March 10	March 11	April 7	March 16	April 7
New Mexico	March 11	March 25	March 24	March 16	March 24
Arkansas	March 11	March 24	April 5	March 17	April 5
North Dakota	March 11	March 27	March 20	March 16	March 20
Delaware	March 11	March 26	March 24	March 16	March 24
Wyoming	March 11	April 13	March 28	March 16	March 28
Mississippi	March 11	March 19	April 3	March 16	April 3
Alaska	March 12	March 28	March 28	March 16	March 28
Maine	March 12	March 27	April 2	March 31	April 2
Alabama	March 13	March 25	March 28	March 16	March 28
Montana	March 13	March 28	March 28	March 16	March 28
Idaho	March 13	March 26	March 25	March 23	March 25
West Virginia	March 17	March 30	March 24	March 16	March 24

Data sources: Data on COVID-19 cases and deaths are collected from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. These data can be downloaded at https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data. Shelter-in-place, school closure, and business closure dates are collected from National Governors' Association. The underlying data can be found at https://www.nga.org/coronavirus/#states.

Table 2: Examples of Top and Bottom Occupations by Work-from-Home (WFH) Capacity

Occupation Discription	WFH index	Percent of female	black	non-college	below 50	immigrant
Top 20 work-from-home occupations:						
Managers, all other	1.00	35.75	5.60	42.75	57.81	12.80
Elementary and middle school teachers	1.00	79.14	6.93	5.27	67.74	6.49
Secretaries and administrative assistants	1.00	95.11	7.25	78.14	51.24	7.90
Accountants and auditors	1.00	61.69	6.59	21.07	60.79	15.83
Postsecondary teachers	1.00	49.70	7.44	9.80	59.29	21.22
Computer scientists	1.00	29.64	5.30	36.31	73.19	17.73
Sales representatives	1.00	27.15	3.09	52.49	58.02	9.05
First-line supervisors of office workers	1.00	62.08	9.51	64.92	58.11	10.31
Bookkeeping and accounting clerks	1.00	88.04	10.36	80.25	47.38	10.12
Office clerks, general	1.00	82.26	6.01	79.42	60.34	11.25
Chief executives	1.00	25.02	2.74	31.21	41.86	12.60
Childcare workers	1.00	93.69	3.54	83.91	70.23	17.77
Lawyers	1.00	36.50	4.19	1.81	55.37	6.56
Software developers	1.00	20.18	12.49	16.49	76.77	35.72
Financial managers	1.00	54.08	10.83	37.16	63.43	13.38
Teacher assistants	1.00	89.58	6.18	75.88	59.80	12.77
Marketing and sales managers	1.00	47.33	3.74	29.18	70.19	10.53
Human resources workers	1.00	69.87	11.20	41.03	68.98	8.70
Other teachers and instructors	1.00	61.83	8.37	48.50	66.65	11.28
Management analysts	1.00	42.39	5.52	22.32	56.89	14.76
Average	1.00	59.79	6.72	41.86	60.51	12.57
Bottom 20 work-from-home occupations:						
Electrical power-line installers	0.00	1.11	4.87	94.39	71.95	4.23
Boilermakers	0.00	3.01	6.94	97.70	61.98	7.84
Heating and air conditioning mechanics	0.08	1.21	5.04	95.01	68.55	12.74
Firefighters	0.08	4.64	5.76	79.11	83.36	2.72
Structural iron and steel workers	0.08	2.37	5.23	95.94	72.79	12.47
Millwrights	0.08	1.92	2.84	96.12	54.51	3.40
Derrick and rotary drill operators	0.08	2.13	4.54	92.83	83.39	8.24
Production workers, all other	0.17	28.12	12.65	93.59	65.37	18.46
Pipelayers, plumbers, and pipefitters	0.17	1.50	5.45	95.20	68.04	13.79
Industrial machinery mechanics	0.17	3.16	5.51	94.13	55.11	11.20
Vehicle and mobile equipment mechanics	0.17	1.14	3.34	96.33	63.34	8.47
First-line supervisors of fire fighters	0.17	17.19	11.84	67.86	57.60	5.22
Automotive watercraft service attendants	0.17	16.83	9.67	94.29	79.05	12.58
Pest control workers	0.17	5.33	7.56	89.01	65.92	8.20
Glaziers	0.17	2.18	3.40	95.53	71.44	13.98
Sailors and marine oilers	0.17	8.62	3.69	86.76	77.14	8.36
Earth drillers, except oil and gas	0.17	1.35	9.54	95.11	73.36	6.58
Paving and surfacing equipment operators	0.17	2.93	14.95	97.42	67.47	8.74
Rail-track laying equipment operators	0.25	1.60	7.02	95.99	68.14	9.49
Grounds maintenance workers	0.25	6.91	5.53	92.13	68.36	27.43
Average	0.17	10.57	7.40	92.12	67.25	16.12
All Occupations	0.78	48.05	8.95	64.71	64.29	14.76

Data sources: The WFH index is constructed using occupation attributes from O*NET and employment from OES. Worker characteristics within each occupation are based on data from the 2014-2018 5-year pooled ACS.

Table 3: Examples of Top and Bottom Occupations by Physical Proximity (HPP)

Occupation Discription	HPP index	Percent of female	black	non-college	below 50	immigrant
Top 20 occupations in physical proximity:						
Physical therapists	1.00	70.12	3.04	5.98	75.17	13.56
Dental hygienists	1.00	95.99	2.70	64.53	67.63	8.27
Dentists	0.99	28.73	2.71	0.14	48.77	21.19
Dancers and choreographers	0.99	79.64	12.11	74.39	94.11	11.98
Dental assistants	0.99	94.78	5.87	90.32	78.30	15.58
Radiation therapists	0.98	69.60	4.93	50.52	67.40	8.50
Emergency medical technicians	0.96	31.03	5.54	82.13	84.85	4.62
Chiropractors	0.96	29.65	1.41	3.33	59.67	8.42
Flight attendants	0.95	73.70	14.48	65.75	53.55	14.87
First-line supervisors of food servers	0.95	58.97	11.78	86.72	75.42	14.12
Actors	0.94	38.92	6.76	29.16	74.54	10.94
Barbers	0.94	24.42	24.04	95.22	59.72	19.20
Podiatrists	0.94	25.66	0.85	0.44	46.49	9.98
Physical therapist assistants and aides	0.94	72.26	5.30	73.55	76.09	8.54
Miscellaneous health technicians	0.93	64.24	15.78	67.11	65.61	15.46
Respiratory therapists	0.92	64.71	10.51	70.61	62.21	12.63
Exercise physiologists	0.92	80.46	8.15	15.27	71.06	10.06
Hairdressers and cosmetologists	0.91	91.70	8.44	94.55	66.83	15.13
Miscellaneous personal appearance workers	0.91	86.07	2.98	89.34	76.82	61.38
Veterinarians	0.89	58.04	1.26	0.16	61.01	6.93
Average	0.94	69.90	7.63	66.17	70.06	16.87
Bottom 20 occupations in physical proximity:						
Logging workers	0.00	2.53	5.62	95.42	63.29	4.79
Petroleum engineers	0.17	11.86	3.33	18.24	72.01	18.73
Economists	0.17	31.06	4.17	0.53	66.39	28.24
Refuse and recyclable material collectors	0.17	10.58	15.88	95.66	65.53	16.75
Writers and authors	0.18	59.98	3.83	17.84	59.99	7.03
Computer and information scientists	0.20	29.64	7.44	36.31	73.19	17.73
Industrial truck and tractor operators	0.21	7.55	18.37	96.95	68.09	17.02
Lawyers	0.22	36.50	4.19	1.81	55.37	6.56
Food processing machine operators	0.22	32.34	8.13	88.72	69.79	16.48
Pressers, textile, garment workers	0.23	65.57	16.28	96.33	60.96	41.30
Actuaries	0.23	33.92	1.74	2.61	78.00	19.38
Miscellaneous agricultural workers	0.23	21.12	2.66	93.77	72.76	39.14
Sales engineers	0.23	7.21	1.93	30.29	62.56	12.96
Personal financial advisors	0.24	30.24	4.20	19.20	60.78	10.20
Meter readers, utilities	0.24	15.55	12.24	91.02	64.82	5.17
Payroll and timekeeping clerks	0.25	88.64	8.66	77.59	54.73	8.78
Pumping station operators	0.26	3.91	5.45	91.43	61.74	4.86
Statisticians	0.27	46.70	4.95	7.82	75.42	25.64
Computer programmers	0.27	21.97	3.56	28.75	66.05	24.27
Paralegals and legal assistants	0.28	85.01	7.27	54.86	63.61	9.60
Average	0.22	33.25	6.50	55.83	44.17	17.17
All Occupations	0.55	48.05	8.95	64.71	64.29	14.76

Data sources: The PP index is constructed using occupation attributes from O*NET and employment from OES. Worker characteristics within each occupation are based on data from the 2014-2018 5-year pooled ACS.

Table 4: Summary Statistics of Main Variables

	Mean	S.D.	Min	Max	No. of Obs.
COVID-19 reported cases	64.60	1,337.94	0	167,478	380,074
Job Characteristics					
Work-from-home (WFH) index	0.74	0.03	0.68	0.92	3,142
High physical proximity (HPP) index	0.56	0.01	0.45	0.60	3,142
Social distancing, work and unemployment					
Percent of devices stay at home	27.78	7.96	1.12	82.76	38,0074
Percent of devices full-time at work	5.40	3.50	0.48	35.71	380,074
Percent of devices part-time at work	9.11	4.19	0.66	56.06	380,074
Unemployment rate (% weekly, by state)	3.34	4.07	0.37	25.20	867
Demographic and socioeconomic characteristics					
Percent male	49.96	1.29	46.57	55.07	3,142
Percent black	9.11	13.16	0.19	70.70	3,142
Percent Asian	2.01	6.27	0.01	73.17	3,142
Percent Hispanic	9.93	13.42	0.57	95.61	3,142
Percent above age 60	24.14	4.05	10.52	52.98	3,142
Percent College degree or higher	22.41	8.35	9.10	77.44	3,142
Percent immigrants	5.12	5.24	0.39	53.26	3,142
Household income (1,000 dollars)	51.84	12.54	27.97	154.12	3,142
Population density (1,000/square mile)	0.27	1.79	0.00	71.34	3,142
Health insurance coverage (%)	89.22	4.92	69.16	98.04	3,142
High speed internet coverage (%)	58.97	11.29	23.26	92.19	3,142
Vote for Republican (%)	63.26	15.69	4.09	96.03	3,114
COVID case density (/1,000 persons)	0.25	1.33	0	102.83	380,074

Data source: Data on COVID-19 cases are collected from the CSSE at Johns Hopkins University. The WFH and HPP indices are constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. County-level 2016 Presidential election results are taken from the MIT Election Data and Science Lab. All other socioeconomic and demographic characteristics of each county are constructed using data from the ACS.

Table 5: Effects of the COVID-19 Pandemic by Local Jobs' Work-From-Home Capacity

	% Stay-at-home		% Full-time at work		% Part-time at work		% Unemployment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event dummy	9.054***	8.961***	-3.437***	-3.421***	-4.868***	-4.851***	6.390***	4.043***
	(0.388)	(0.388)	(0.170)	(0.171)	(0.189)	(0.191)	(0.313)	(0.322)
Event × WFH	7.431***	7.249***	-0.145	-0.113	-0.676***	-0.643**	-2.022***	-1.430***
	(0.631)	(0.632)	(0.289)	(0.291)	(0.192)	(0.193)	(0.424)	(0.391)
WFH dummy	-0.897*	-2.463***	0.296*	0.148	0.046	0.348**	1.453***	-0.035
	(0.337)	(0.206)	(0.132)	(0.138)	(0.101)	(0.129)	(0.184)	(0.458)
% Male		22.762**		-14.194***		-17.336***		55.280
		(7.343)		(2.012)		(2.974)		(44.021)
% Black		3.747**		-0.574		-0.897		-0.731
		(1.245)		(0.363)		(0.543)		(2.826)
% Asian		6.926***		-0.523		-2.540***		-8.672
		(1.947)		(0.634)		(0.717)		(8.220)
% Hispanic		0.002		-0.893*		-0.395		0.757
		(1.729)		(0.357)		(0.431)		(2.777)
% Above 60		9.925***		-1.150		-5.110***		-7.044
		(2.164)		(0.793)		(1.063)		(5.975)
% College		-8.640***		-0.821		0.731		-21.437**
		(2.222)		(0.524)		(0.586)		(6.495)
% Immigrant		9.278		2.314***		0.065		-12.600**
		(4.778)		(0.609)		(0.905)		(3.833)
Income		-0.013		0.015***		0.019***		-0.194
		(0.021)		(0.004)		(0.005)		(0.105)
Population density		-0.003		-0.000		0.002		0.001
		(0.017)		(0.005)		(0.004)		(0.001)
Health insurance		10.238		1.462		-1.025		2.084
		(7.241)		(1.528)		(2.539)		(8.043)
Internet access		12.406***		-0.664		-2.874***		5.986
		(1.492)		(0.353)		(0.669)		(4.419)
Republican vote		-6.357***		0.780*		3.572***		-13.018***
		(1.192)		(0.317)		(0.393)		(3.597)
Case density		0.198		-0.035		-0.036		1.315***
		(0.105)		(0.022)		(0.021)		(0.065)
State dummies	yes	yes	yes	yes	yes	yes		
Weekday dummies	yes	yes	yes	yes	yes	yes		
No. of obs.	379,698	379,698	379,698	379,698	379,698	379,698	850	850
R-squared	0.734	0.754	0.653	0.659	0.730	0.743	0.319	0.578

Note: The declaration of national emergency is used to indicate the outbreak of the pandemic. The event dummy equals 1 after the declaration and equals 0 otherwise. The WFH index is constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The WFH dummy equals 1 if the WFH index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. County-level 2016 Presidential election results are taken from the MIT Election Data and Science Lab. Data on COVID-19 cases are collected from the CSSE at Johns Hopkins University. All other socioeconomic and demographic characteristics are constructed using data from the ACS. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 6: Effects of the COVID-19 Pandemic by Local Jobs' Physical Proximity

	% Stay-at-home		% Full-time at work		% Part-time at work		% Unemployment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event dummy	16.962***	16.659***	-3.786***	-3.737***	-5.764***	-5.714***	6.047***	3.232***
	(0.648)	(0.651)	(0.356)	(0.362)	(0.248)	(0.253)	(0.253)	(0.260)
Event × HPP	-4.375***	-4.235***	0.681**	0.659**	0.940***	0.917***	1.177***	-0.883*
	(0.807)	(0.832)	(0.219)	(0.220)	(0.142)	(0.142)	(0.224)	(0.358)
HPP dummy	1.184***	2.122***	-0.600***	-0.413***	-0.453***	-0.411***	-1.259**	-0.346
	(0.230)	(0.277)	(0.091)	(0.074)	(0.107)	(0.092)	(0.431)	(0.370)
% Male		18.576*		-14.120***		-17.629***		1.114
		(7.254)		(2.194)		(3.052)		(49.018)
% Black		4.147***		-0.634		-0.895		-1.385
		(1.121)		(0.362)		(0.517)		(2.848)
% Asian		6.564**		-0.425		-2.521**		-4.568
		(1.896)		(0.644)		(0.749)		(8.389)
% Hispanic		0.336		-0.881**		-0.365		0.768
		(1.566)		(0.311)		(0.446)		(2.788)
% Above 60		8.825***		-0.931		-5.092***		0.992
		(2.325)		(0.837)		(1.086)		(6.463)
% College		-7.135***		-0.993*		0.763		-32.424***
		(1.861)		(0.426)		(0.616)		(6.405)
% Immigrant		9.162		2.208***		0.009		-10.775**
		(4.580)		(0.574)		(0.910)		(3.904)
Income		-0.014		0.013**		0.019***		-0.106
		(0.020)		(0.004)		(0.005)		(0.111)
Population density		-0.008		-0.000		0.002		0.001
		(0.017)		(0.005)		(0.004)		(0.001)
Health insurance		10.064		1.506		-1.013		10.226
		(7.032)		(1.494)		(2.533)		(7.242)
Internet access		13.114***		-0.436		-2.703***		7.162
		(1.611)		(0.362)		(0.658)		(4.445)
Republican vote		-5.993***		0.685*		3.553***		-9.574**
		(1.097)		(0.315)		(0.379)		(3.545)
Case density		0.203		-0.033		-0.034		1.324***
		(0.109)		(0.022)		(0.021)		(0.066)
State dummies	yes	yes	yes	yes	yes	yes		
Weekday dummies	yes	yes	yes	yes	yes	yes		
No. of obs.	379,698	379,698	379,698	379,698	379,698	379,698	850	850
R-squared	0.725	0.749	0.656	0.661	0.731	0.745	0.319	0.575

Note: The declaration of national emergency is used to indicate the outbreak of the pandemic. The event dummy equals 1 after the declaration and equals 0 otherwise. The HPP index is constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The HPP dummy equals 1 if the HPP index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. County-level 2016 Presidential election results are taken from the MIT Election Data and Science Lab. Data on COVID-19 cases are collected from the CSSE at Johns Hopkins University. All other socioeconomic and demographic characteristics are constructed using data from the ACS. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 7: Effects of the COVID-19 Pandemic by Local Job Characteristics (WFH and HPP)

	% Stay-at-home		% Full-time at work		% Part-time at work		% Unemployment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event dummy	11.155***	10.996***	-3.911***	-3.883***	-5.453***	-5.426***	4.950***	5.191***
	(0.606)	(0.591)	(0.240)	(0.242)	(0.190)	(0.192)	(0.599)	(0.469)
Event × WFH	6.198***	6.065***	0.133	0.157	-0.332	-0.309	-0.610	-2.238***
	(0.748)	(0.764)	(0.249)	(0.253)	(0.177)	(0.178)	(0.568)	(0.451)
Event × HPP	-3.136***	-3.032***	0.708***	0.690***	0.874***	0.856***	0.094	-1.438***
	(0.770)	(0.800)	(0.195)	(0.197)	(0.128)	(0.128)	(0.535)	(0.426)
WFH dummy	-0.465	-1.986***	0.064	0.039	-0.145	0.214	-0.212	0.320
	(0.318)	(0.264)	(0.126)	(0.124)	(0.095)	(0.122)	(0.364)	(0.479)
HPP dummy	1.101***	1.630***	-0.587***	-0.426***	-0.483***	-0.386***	-0.567	-0.603
	(0.205)	(0.274)	(0.083)	(0.072)	(0.105)	(0.091)	(0.344)	(0.387)
% Male		21.031**		-13.575***		-17.153***		-14.064
		(7.273)		(2.151)		(3.070)		(48.965)
% Black		4.006***		-0.667		-0.925		-1.954
		(1.126)		(0.363)		(0.522)		(2.806)
% Asian		6.626**		-0.413		-2.512**		0.253
		(1.910)		(0.622)		(0.735)		(8.463)
% Hispanic		0.136		-0.936**		-0.417		0.696
		(1.560)		(0.308)		(0.435)		(2.737)
% Above 60		9.161***		-0.867		-5.041***		-6.351
		(2.267)		(0.850)		(1.099)		(6.569)
% College		-7.760***		-1.136*		0.637		-25.621***
		(1.964)		(0.442)		(0.622)		(5.351)
% Immigrant		9.354*		2.273***		0.075		-11.854**
		(4.494)		(0.573)		(0.896)		(3.855)
Income		-0.010		0.014**		0.019***		-0.090
		(0.020)		(0.004)		(0.005)		(0.110)
Population density		-0.004		0.000		0.002		0.001
		(0.017)		(0.005)		(0.004)		(0.001)
Health insurance		10.044		1.522		-0.991		2.915
		(7.015)		(1.492)		(2.530)		(7.937)
Internet access		12.260***		-0.614		-2.855***		10.141*
		(1.537)		(0.381)		(0.688)		(4.485)
Republican vote		-6.051***		0.670*		3.540***		-11.767**
		(1.103)		(0.316)		(0.378)		(3.603)
Case density		0.190		-0.033		-0.033		1.380***
		(0.103)		(0.022)		(0.021)		(0.066)
State dummies	yes	yes	yes	yes	yes	yes		
Weekday dummies	yes	yes	yes	yes	yes	yes		
No. of obs.	379,698	379,698	379,698	379,698	379,698	379,698	850	850
R-squared	0.739	0.759	0.656	0.661	0.732	0.745	0.322	0.591

Note: The declaration of national emergency is used to indicate the outbreak of the pandemic. The event dummy equals 1 after the declaration and equals 0 otherwise. The WFH and HPP indices are constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The WFH/HPP dummy equals 1 if the WFH/HPP index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. County-level 2016 Presidential election results are taken from the MIT Election Data and Science Lab. Data on COVID-19 cases are collected from the CSSE at Johns Hopkins University. All other socioeconomic and demographic characteristics are constructed using data from the ACS. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 8: Effects of the COVID-19 Pandemic by WFH in Different Regions

	Education		Income		Internet access		Republican vote	
	high	low	high	low	high	low	high	low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: % Stay-at-home								
Event	9.763***	8.749***	10.330***	8.055***	10.314***	8.191***	8.374***	9.464***
	(0.459)	(0.380)	(0.382)	(0.315)	(0.475)	(0.316)	(0.324)	(0.620)
Event × WFH	6.879***	3.236***	6.795***	2.841***	6.345***	2.167**	2.566***	7.225***
	(0.750)	(0.843)	(0.637)	(0.425)	(0.708)	(0.697)	(0.507)	(0.728)
p (high=low)	0.0003		0.0000		0.0005		0.0002	
Panel B: % Full-time at work								
Event	-4.078***	-3.245***	-4.080***	-3.067***	-3.644***	-3.284***	-3.429***	-3.349***
	(0.261)	(0.158)	(0.249)	(0.141)	(0.223)	(0.176)	(0.143)	(0.264)
Event × WFH	0.446	0.664	0.427	0.209	0.084	0.103	-0.155	-0.174
	(0.365)	(0.428)	(0.381)	(0.137)	(0.369)	(0.280)	(0.192)	(0.319)
p (high=low)	0.6584		0.6956		0.9746		0.9714	
Panel C: % Part-time at work								
Event	-5.146***	-4.731***	-5.192***	-4.638***	-4.752***	-4.872***	-4.895***	-4.708***
	(0.221)	(0.209)	(0.189)	(0.229)	(0.228)	(0.233)	(0.224)	(0.222)
Event × WFH	-0.451	0.205	-0.466*	0.071	-0.752**	-0.487	-0.676*	-0.771***
	(0.266)	(0.411)	(0.231)	(0.190)	(0.279)	(0.384)	(0.256)	(0.215)
p (high=low)	0.0509		0.0936		0.5362		0.7862	
Panel D: % Unemployment								
Event	4.457***	1.907***	4.482***	1.706***	5.363***	1.027***	1.596***	6.190***
	(0.822)	(0.277)	(0.706)	(0.308)	(0.599)	(0.296)	(0.296)	(0.762)
Event × WFH	-1.392***	-1.154	-1.661*	-0.367	-2.783***	1.029*	-0.149	-3.347***
	(0.389)	(0.868)	(0.749)	(0.447)	(0.656)	(0.400)	(0.396)	(0.810)
p (high=low)	0.8834		0.4190		0.0058		0.0625	

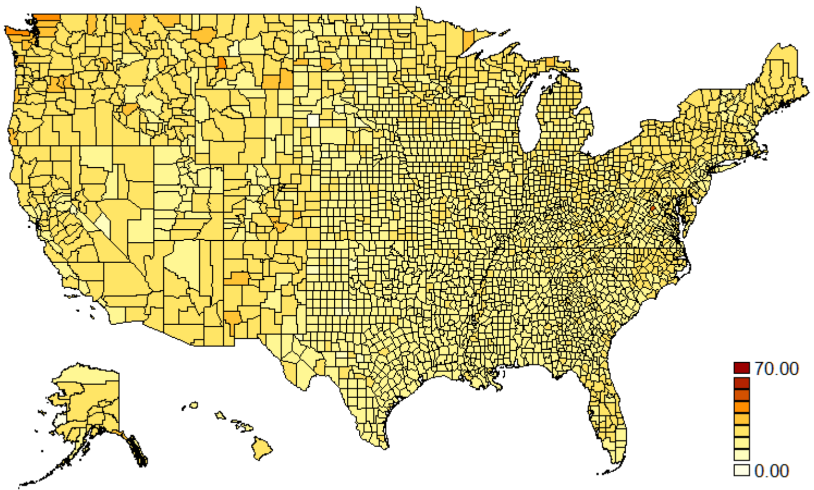
Note: The declaration of national emergency is used to indicate the outbreak of the pandemic. The event dummy equals 1 after the declaration and equals 0 otherwise. The WFH index is constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The WFH dummy equals 1 if the WFH index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. We control for the full set of covariates except for the characteristic used to distinguish different regions and divide the sample, including education, income, high-speed Internet access, and Republic vote share, respectively. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 9: Effects of the COVID-19 Pandemic by HPP in Different Regions

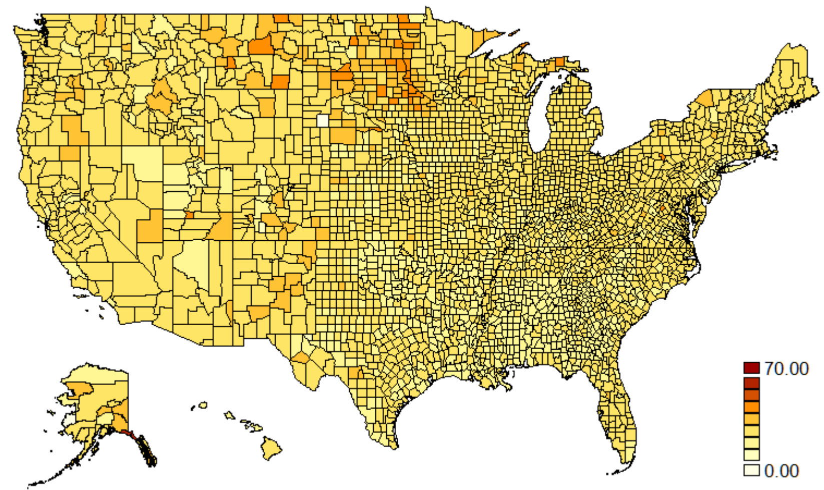
	Education		Income		Internet access		Republican vote	
	high	low	high	low	high	low	high	low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: % Stay-at-home								
Event	17.209***	10.103***	17.263***	9.533***	17.162***	9.651***	11.141***	17.183***
	(0.664)	(0.832)	(0.625)	(0.445)	(0.640)	(0.327)	(0.559)	(0.617)
Event × HPP	-3.253**	0.109	-2.519*	0.288	-3.178**	-0.792	-2.435***	-3.532***
	(1.035)	(0.819)	(1.062)	(0.716)	(0.972)	(0.649)	(0.507)	(0.943)
p (high=low)	0.0278		0.0733		0.1510		0.4979	
Panel B: % Full-time at work								
Event	-3.821***	-2.730***	-3.826***	-2.717***	-3.775***	-3.191***	-3.753***	-3.729***
	(0.350)	(0.458)	(0.378)	(0.267)	(0.373)	(0.297)	(0.163)	(0.393)
Event × HPP	0.730**	-0.307	0.713***	-0.298	0.783***	-0.072	0.410*	0.758**
	(0.234)	(0.313)	(0.198)	(0.232)	(0.222)	(0.264)	(0.164)	(0.234)
p (high=low)	0.0007		0.0004		0.0138		0.3989	
Panel C: % Part-time at work								
Event	-5.825***	-4.438***	-5.832***	-4.373***	-5.774***	-4.861***	-5.658***	-5.711***
	(0.241)	(0.419)	(0.258)	(0.307)	(0.255)	(0.402)	(0.307)	(0.261)
Event × HPP	1.003***	-0.281	0.962***	-0.296	1.158***	-0.313	0.698**	0.995***
	(0.147)	(0.305)	(0.109)	(0.286)	(0.150)	(0.319)	(0.236)	(0.137)
p (high=low)	0.0000		0.0000		0.0000		0.1872	
Panel D: % Unemployment								
Event	3.608***	1.581***	3.183***	2.753***	3.339***	1.912***	2.006***	3.421***
	(0.321)	(0.360)	(0.274)	(0.551)	(0.325)	(0.312)	(0.349)	(0.327)
Event × HPP	-1.904***	-1.101	-1.345*	-1.489*	-0.808	-0.727	-0.719	-0.670
	(0.570)	(0.616)	(0.643)	(0.583)	(0.514)	(0.394)	(0.415)	(0.618)
p (high=low)	0.6635		0.9149		0.9359		0.9657	

Note: The declaration of national emergency is used to indicate the outbreak of the pandemic. The event dummy equals 1 after the declaration and equals 0 otherwise. The HPP index is constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The HPP dummy equals 1 if the HPP index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. We control for the full set of covariates except for the characteristic used to distinguish different regions and divide the sample, including education, income, high-speed Internet access, and Republic vote share, respectively. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

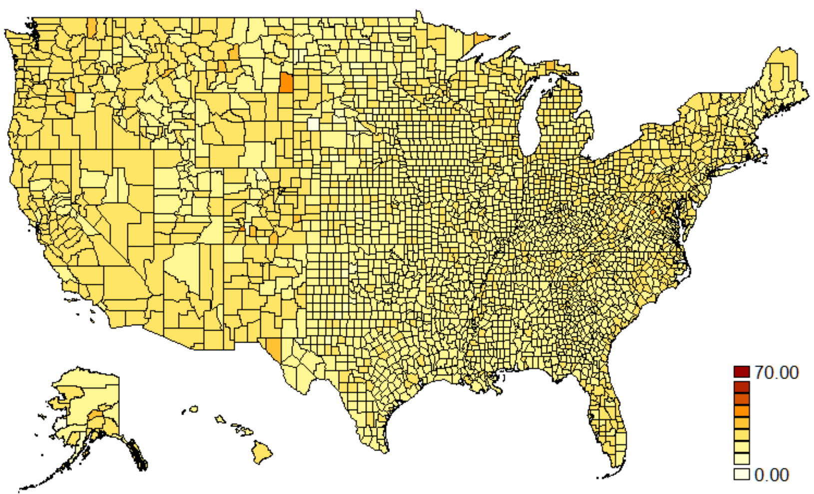
Figure A1: Changes in Percentages of Devices at Home across Counties



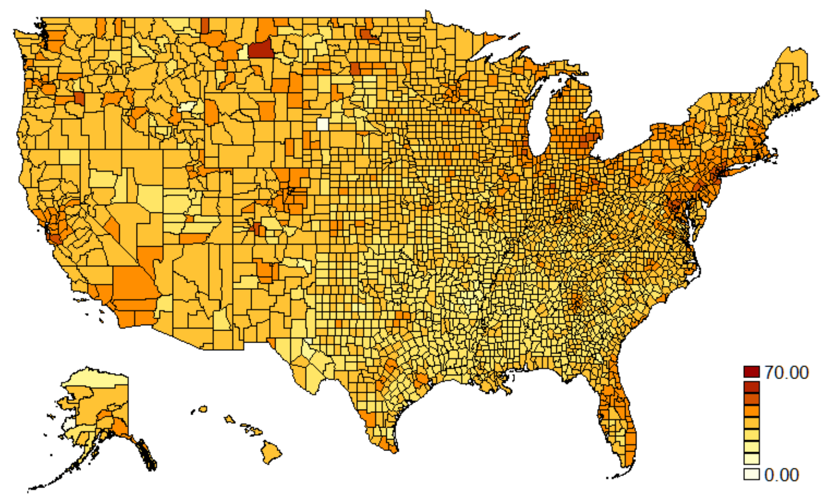
(a) January



(b) February



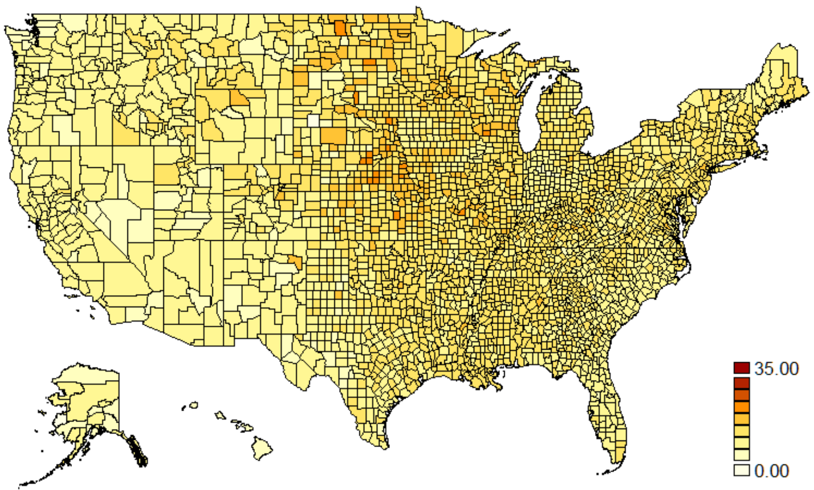
(c) March



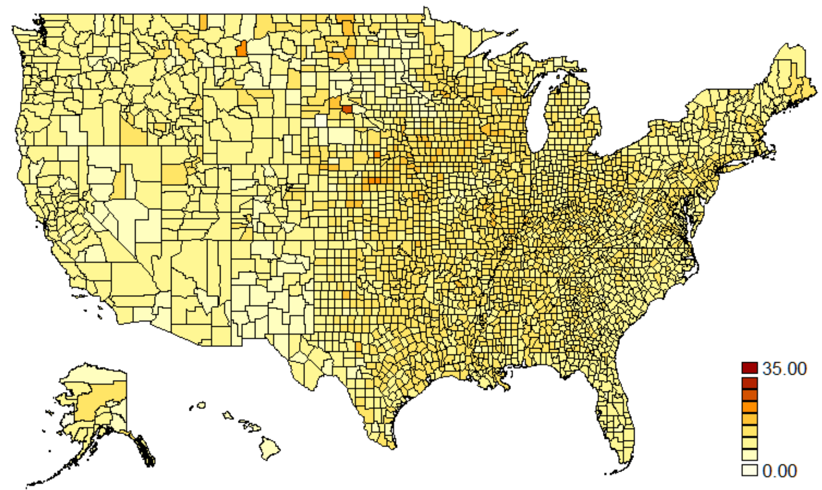
(d) April

Notes: The percentage of devices at home in each county is calculated based on daily data provided by SafeGraph. We present the percentages across counties on the second Wednesday for each month between January and April 2020.

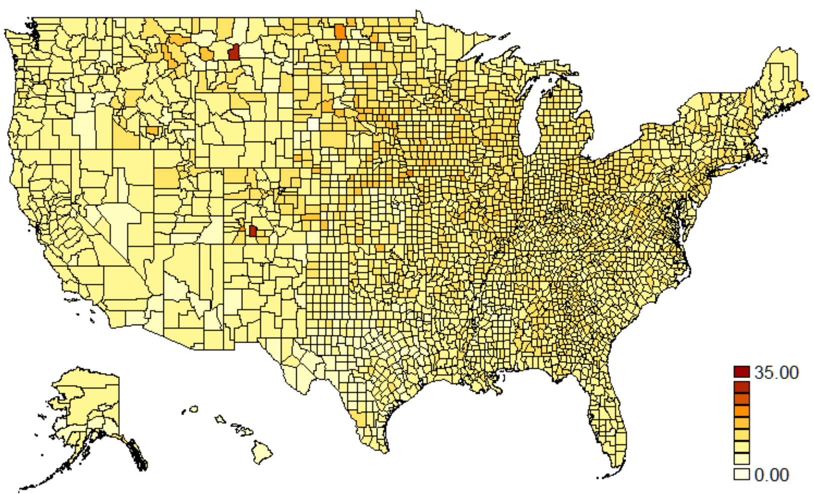
Figure A2: Changes in Percentages of Devices Full-time at Work across Counties



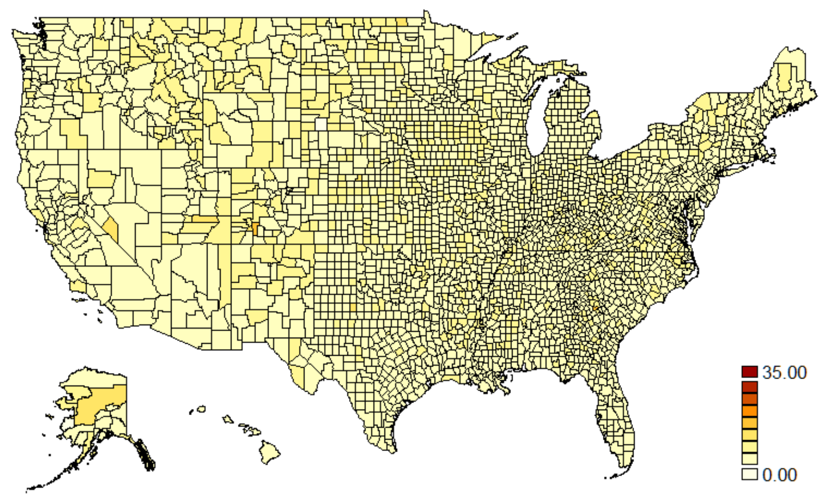
(a) January



(b) February



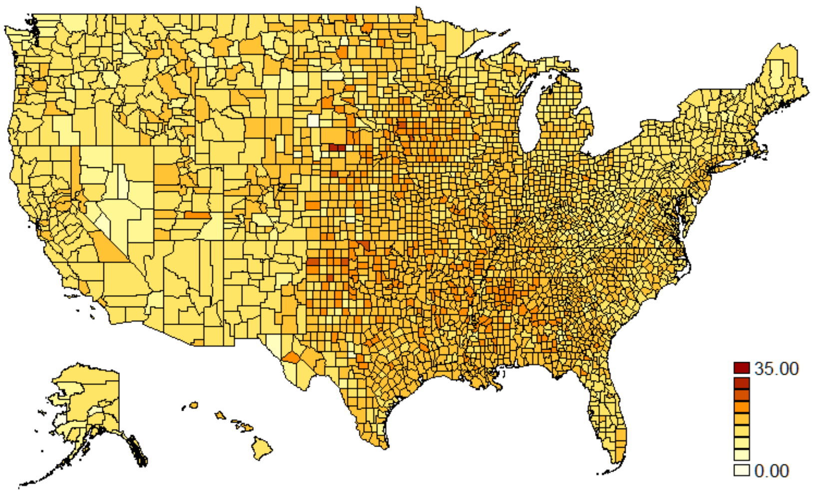
(c) March



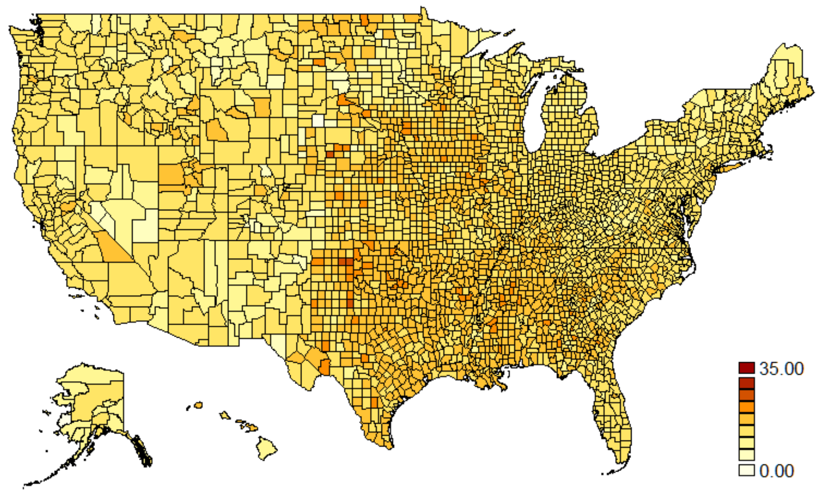
(d) April

Notes: The percentage of devices full-time at work in each county is calculated based on daily data provided by SafeGraph. We present the percentages across counties on the second Wednesday for each month between January and April 2020.

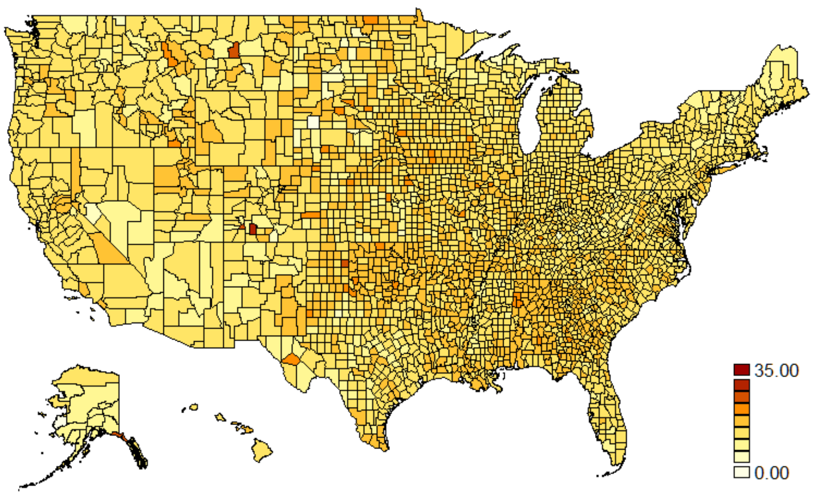
Figure A3: Changes in Percentages of Devices Part-time at Work across Counties



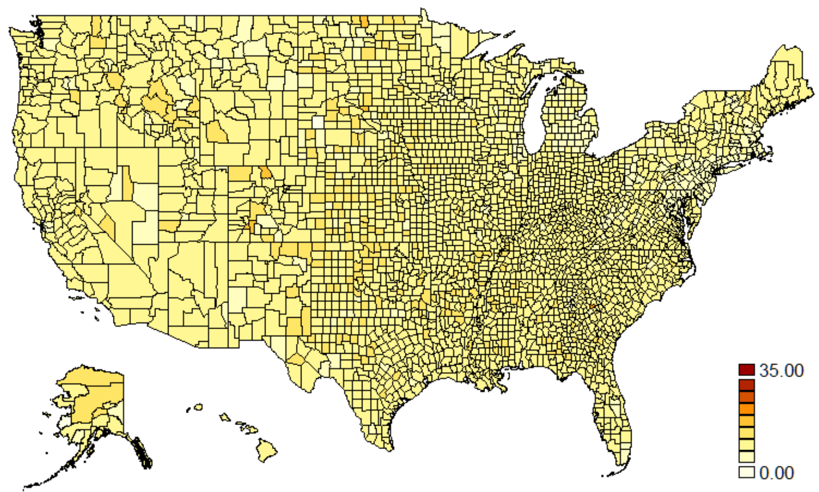
(a) January



(b) February



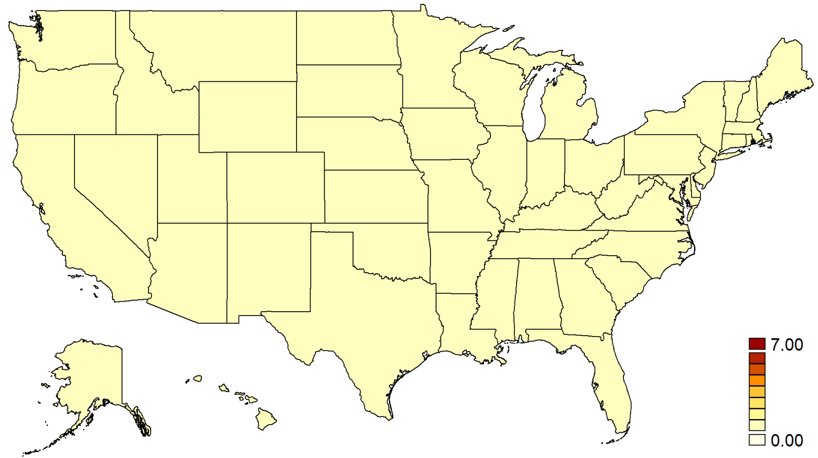
(c) March



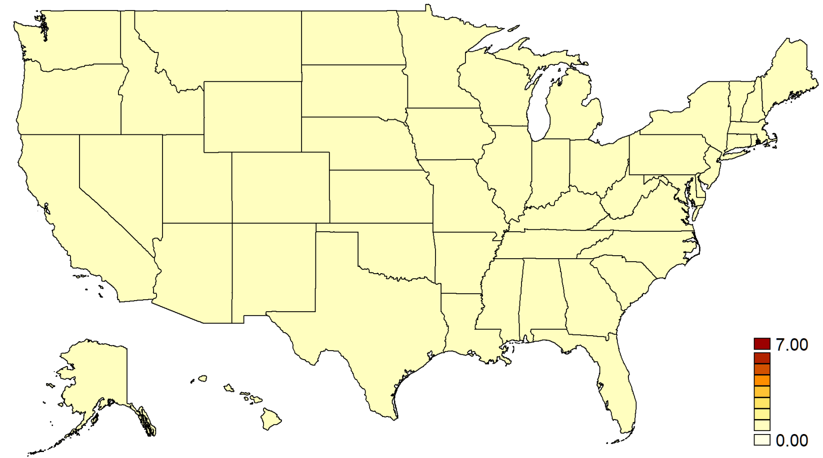
(d) April

Notes: The percentage of devices part-time at work in each county is calculated based on daily data provided by SafeGraph. We present the percentages across counties on the second Wednesday for each month between January and April 2020.

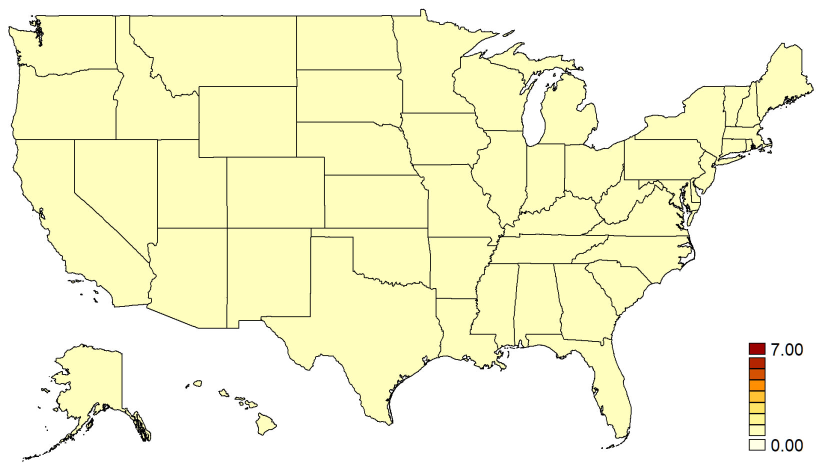
Figure A4: Changes in Unemployment Rates across States



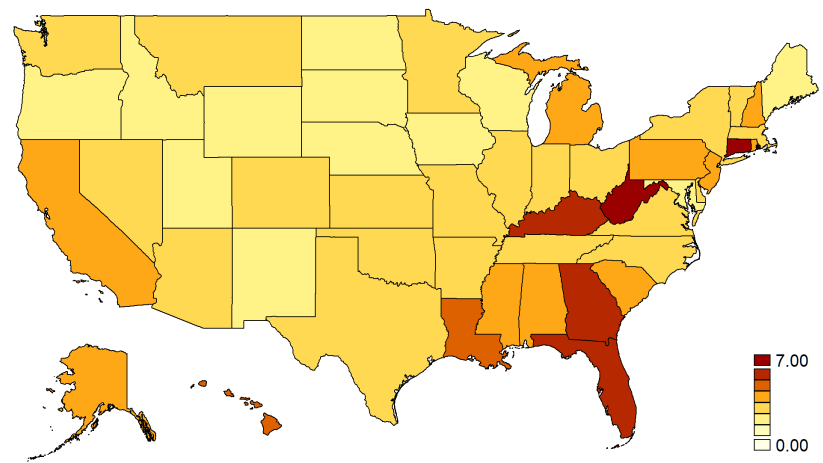
(a) January



(b) February



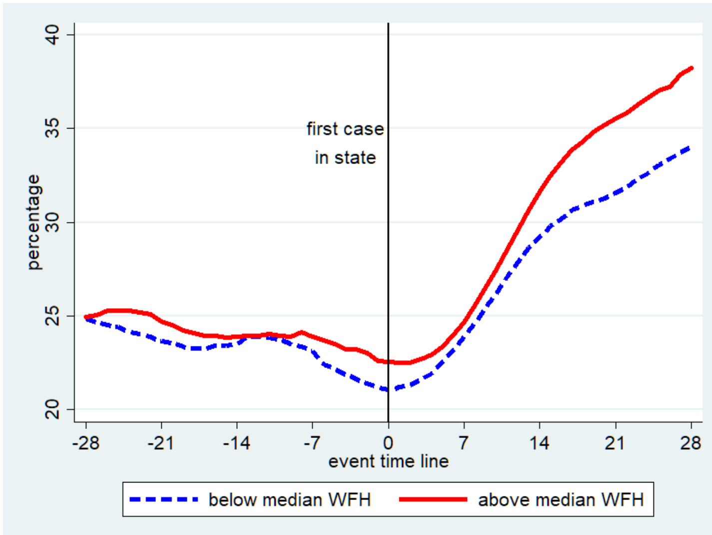
(c) March



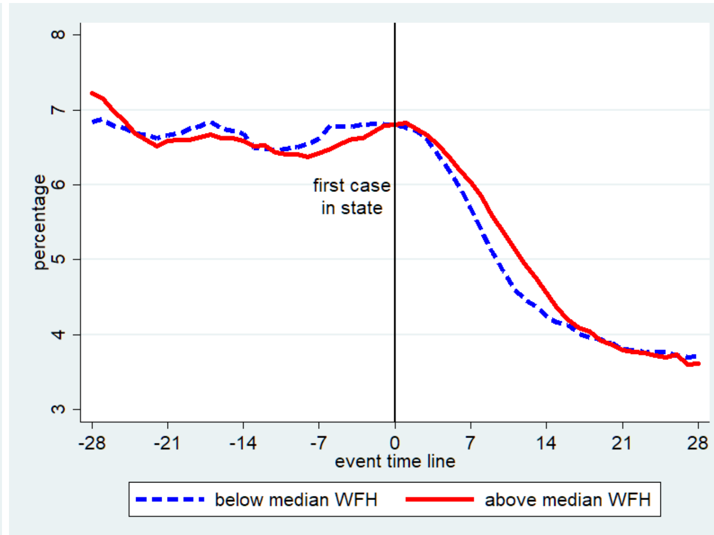
(d) April

Notes: The percentage of unemployment in each state is calculated based on data from Department of Labor. We present the percentages across states on the second weekend for each month between January and April 2020.

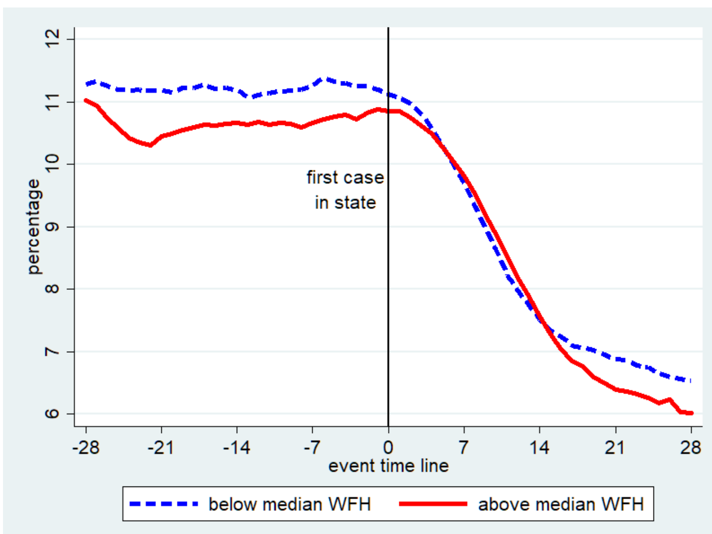
Figure A5: Behavior Changes by Local WFH Index Before and After First Case in State



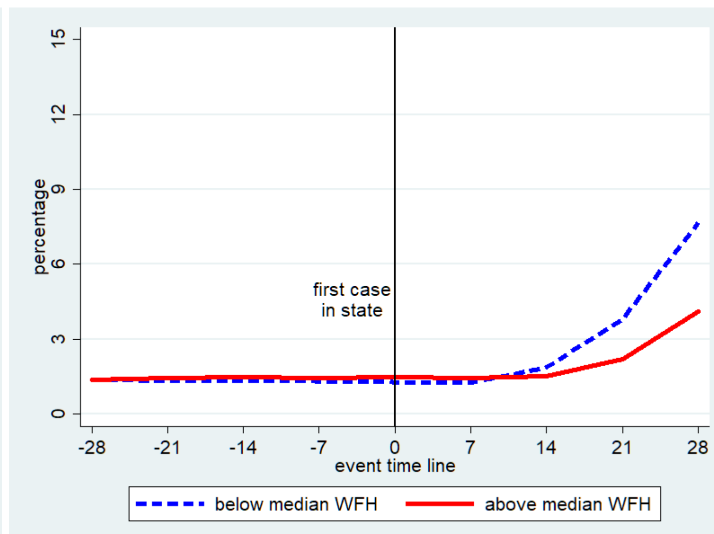
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



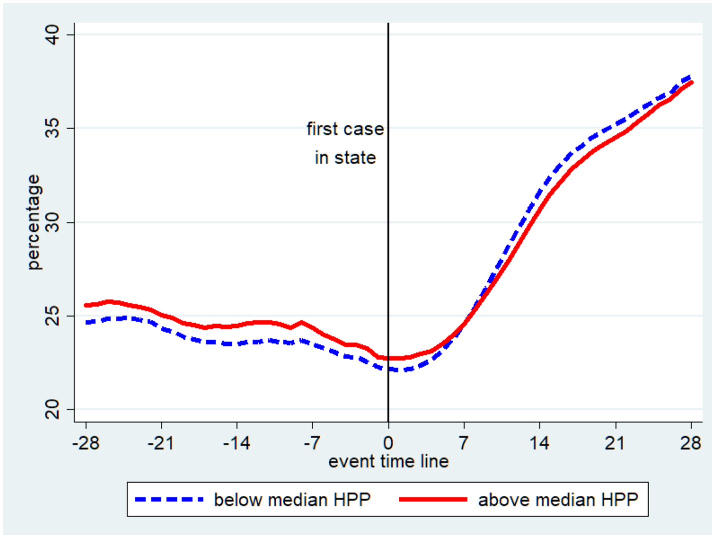
(c) Percent of Devices Part-time at Work



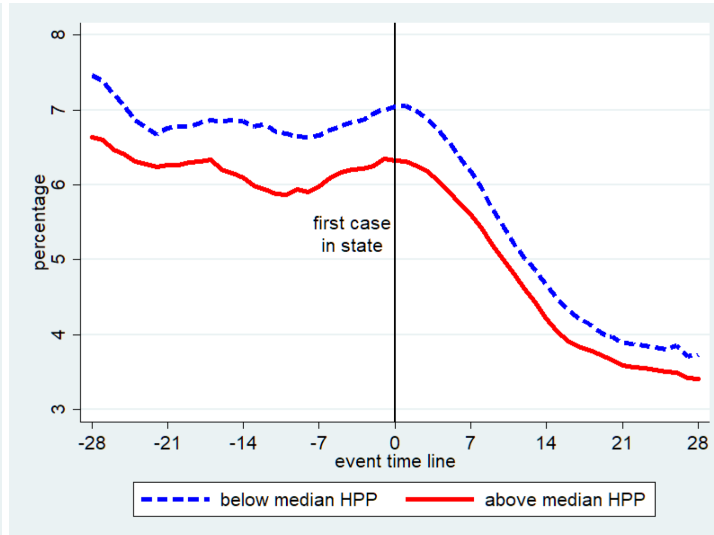
(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

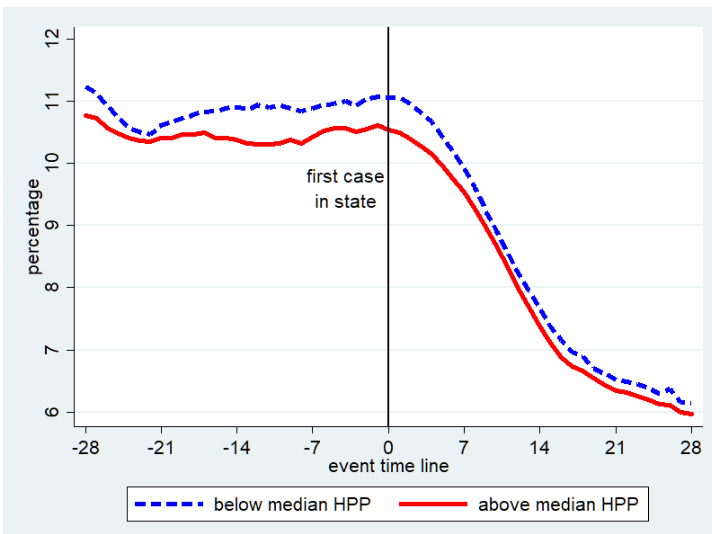
Figure A6: Behavior Changes by Local HPP Index Before and After First Case in State



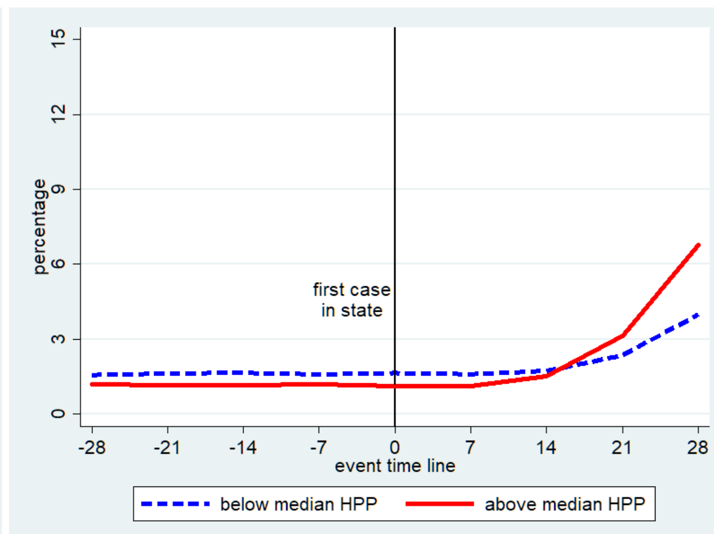
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



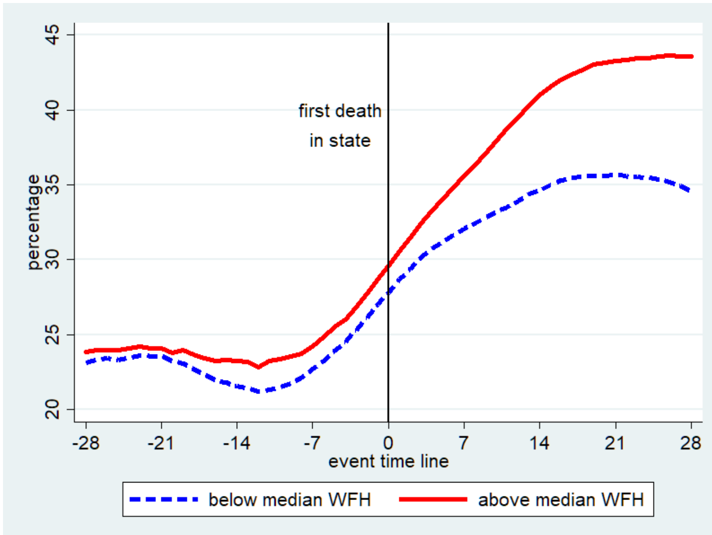
(c) Percent of Devices Part-time at Work



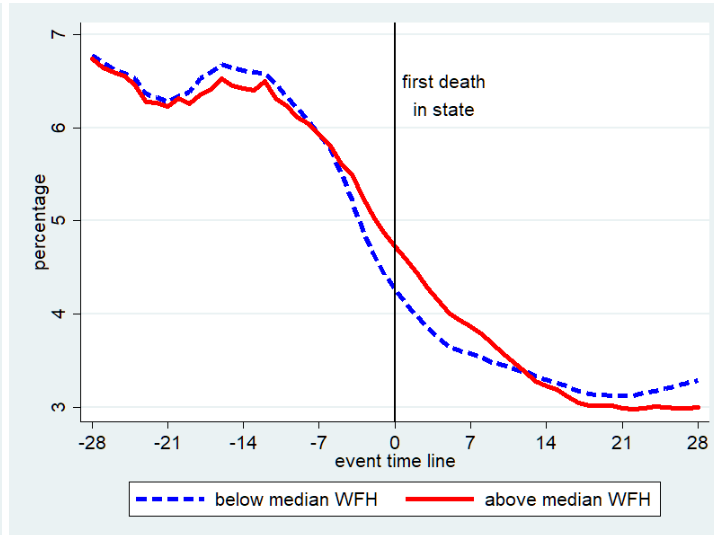
(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

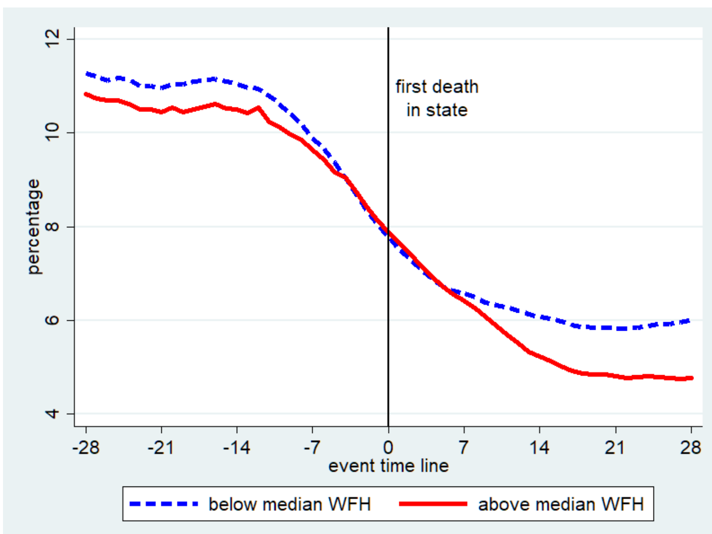
Figure A7: Behavior Changes by Local WFH Index Before and After First Death in State



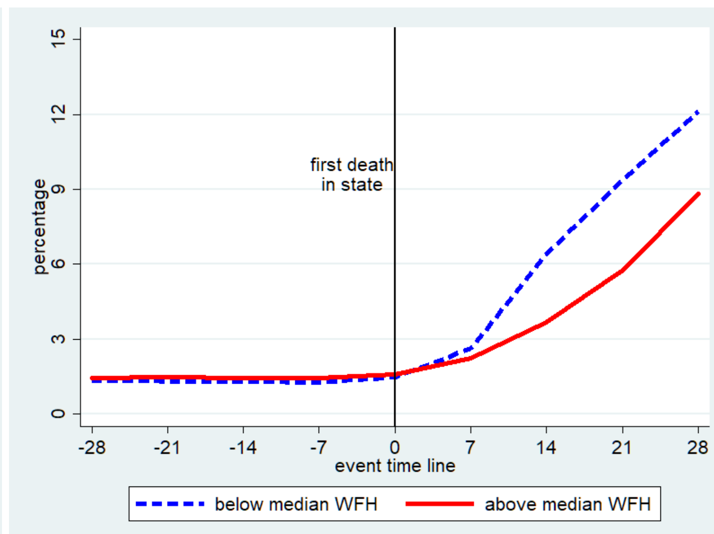
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



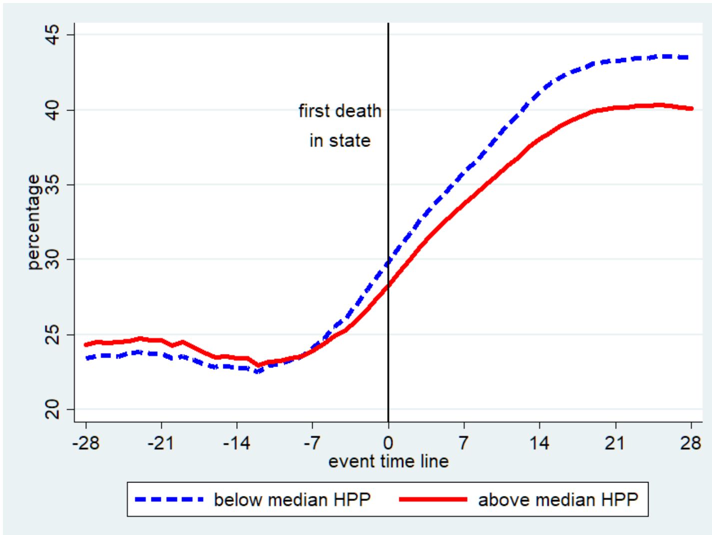
(c) Percent of Devices Part-time at Work



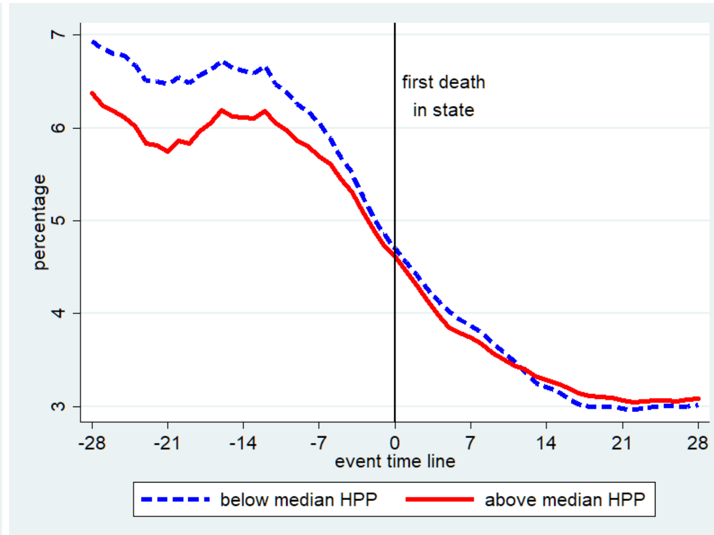
(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

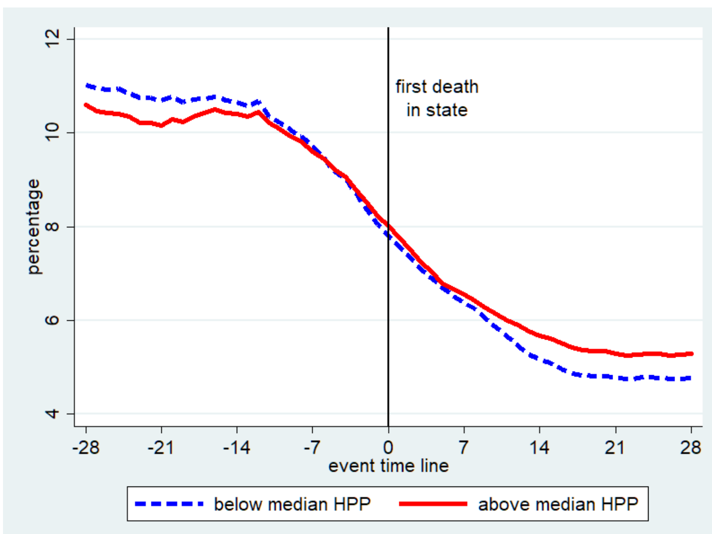
Figure A8: Behavior Changes by Local HPP Index Before and After First Death in State



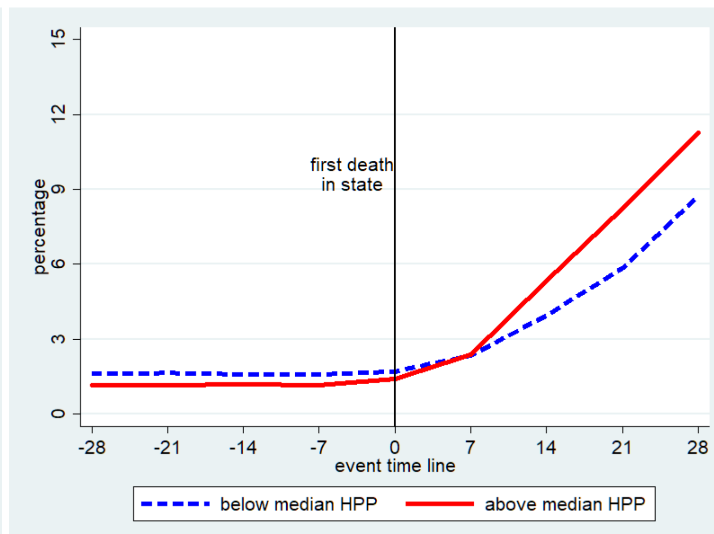
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



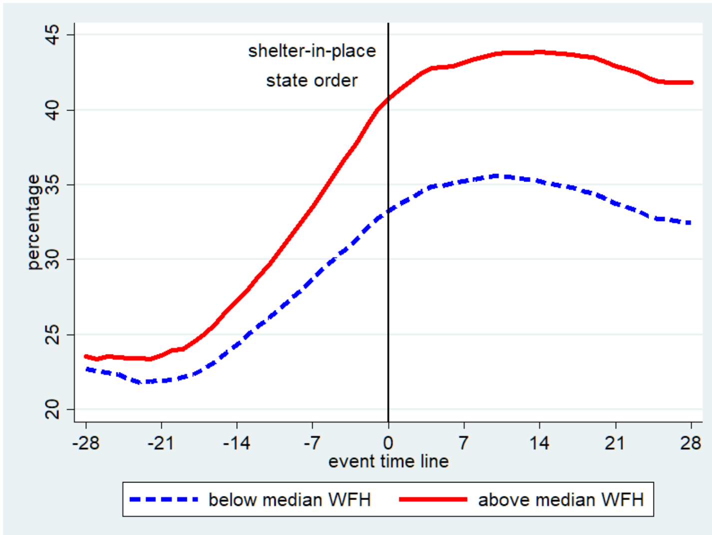
(c) Percent of Devices Part-time at Work



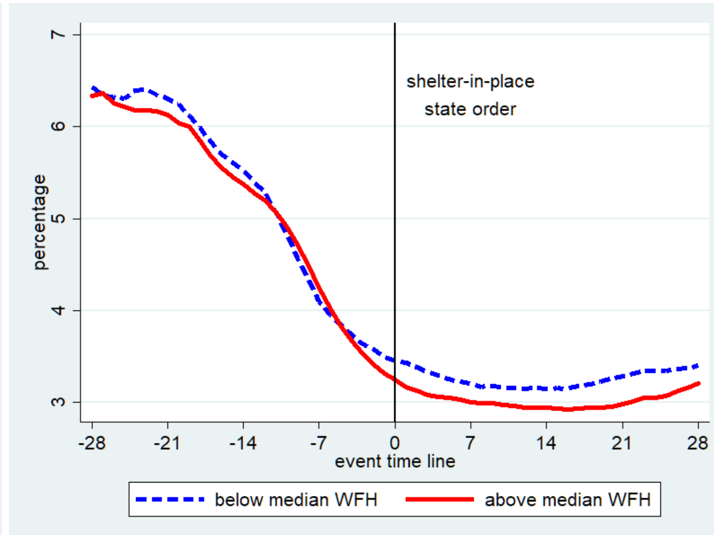
(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

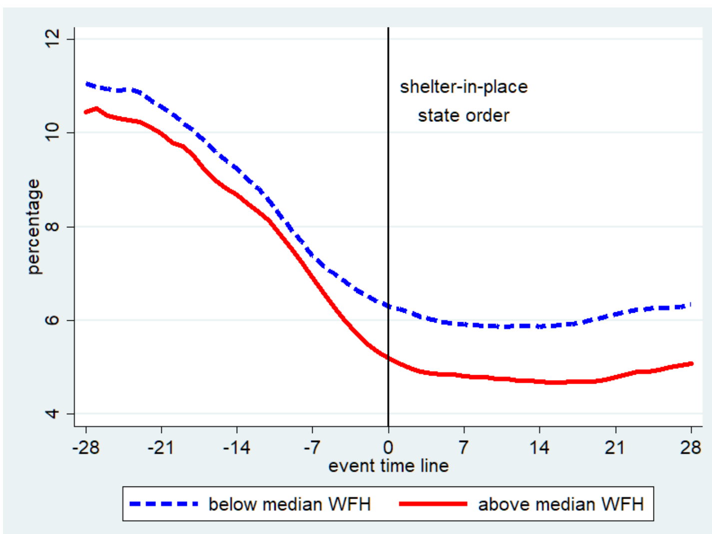
Figure A9: Behavior Changes by Local WFH Index Before and After State Shelter-in-Place Order



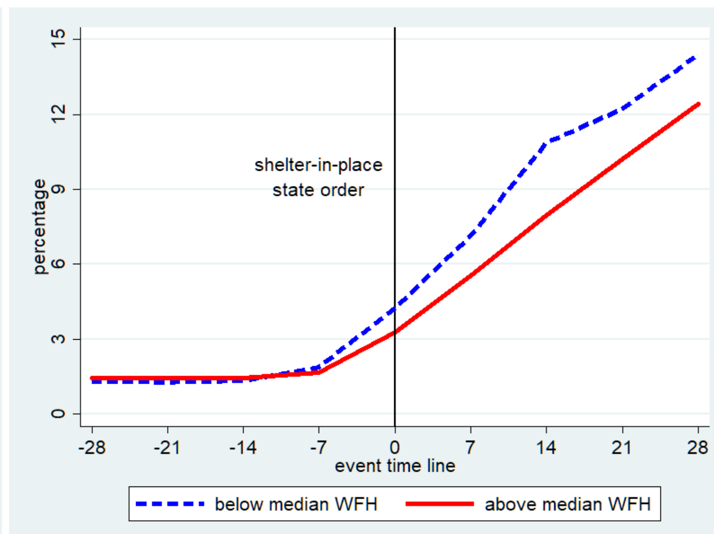
(a) Percent of Devices at Home



(b) Percent of Devices Full-time at Work



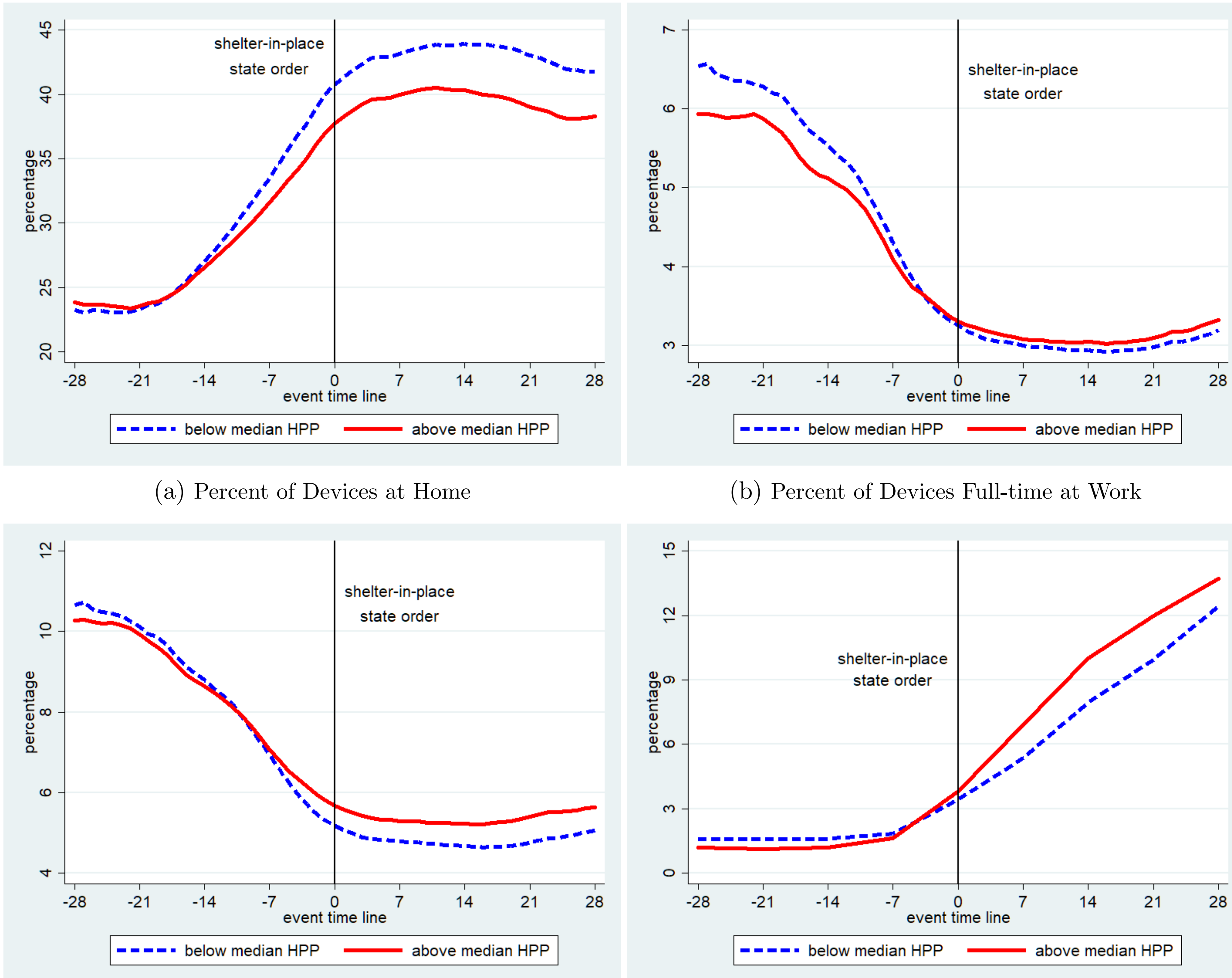
(c) Percent of Devices Part-time at Work



(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

Figure A10: Behavior Changes by Local HPP Index Before and After State Shelter-in-Place Order



(a) Percent of Devices at Home

(b) Percent of Devices Full-time at Work

(c) Percent of Devices Part-time at Work

(d) Percent of Devices Part-time at Work

Notes: Percentages of devices at home, full-time at work, and part-time at work are calculated based on daily data provided by SafeGraph. Unemployment insurance data come from Department of Labor.

Table A1: Effects of the COVID-19 Pandemic by Local Job Characteristics with Alternative Events

	% Stay-at-home		% Full-time at work		% Part-time at work		% Unemployment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: National emergency declaration								
Event dummy	11.155***	10.996***	-3.911***	-3.883***	-5.453***	-5.426***	4.950***	5.191***
	(0.606)	(0.591)	(0.240)	(0.242)	(0.190)	(0.192)	(0.599)	(0.469)
Event × WFH	6.198***	6.065***	0.133	0.157	-0.332	-0.309	-0.610	-2.238***
	(0.748)	(0.764)	(0.249)	(0.253)	(0.177)	(0.178)	(0.568)	(0.451)
Event × HPP	-3.136***	-3.032***	0.708***	0.690***	0.874***	0.856***	0.094	-1.438***
	(0.770)	(0.800)	(0.195)	(0.197)	(0.128)	(0.128)	(0.535)	(0.426)
Panel B: First case in state								
Event dummy	8.570***	8.286***	-3.282***	-3.227***	-4.591***	-4.505***	4.591***	4.730***
	(0.570)	(0.545)	(0.199)	(0.199)	(0.240)	(0.250)	(0.614)	(0.483)
Event × WFH	4.410***	4.112***	0.108	0.147	-0.094	-0.037	-1.091	-2.545***
	(0.661)	(0.682)	(0.221)	(0.221)	(0.266)	(0.261)	(0.583)	(0.462)
Event × HPP	-1.904**	-1.685*	0.473*	0.457*	0.538**	0.478*	0.673	-0.885*
	(0.561)	(0.653)	(0.190)	(0.177)	(0.197)	(0.200)	(0.547)	(0.440)
Panel C: First death in state								
Event dummy	11.578***	11.435***	-3.828***	-3.789***	-5.371***	-5.334***	6.835***	7.028***
	(0.605)	(0.575)	(0.263)	(0.267)	(0.206)	(0.216)	(0.562)	(0.448)
Event × WFH	5.514***	5.340***	0.218	0.235	-0.189	-0.162	-1.691**	-3.298***
	(0.717)	(0.716)	(0.277)	(0.282)	(0.227)	(0.228)	(0.534)	(0.434)
Event × HPP	-2.840***	-2.706***	0.609**	0.594**	0.762***	0.733***	0.353	-1.374***
	(0.728)	(0.746)	(0.220)	(0.221)	(0.158)	(0.162)	(0.496)	(0.406)
Panel D: State shelter-in-place directive								
Event dummy	11.673***	11.628***	-3.695***	-3.671***	-5.155***	-5.149***	7.709***	8.115***
	(0.735)	(0.717)	(0.245)	(0.250)	(0.162)	(0.167)	(0.502)	(0.425)
Event × WFH	6.208***	6.103***	0.133	0.159	-0.353**	-0.326*	-0.782	-2.674***
	(0.874)	(0.879)	(0.227)	(0.232)	(0.127)	(0.129)	(0.481)	(0.422)
Event × HPP	-2.670**	-2.658**	0.631**	0.612**	0.761***	0.751***	1.391**	-0.500
	(0.927)	(0.917)	(0.192)	(0.192)	(0.113)	(0.113)	(0.450)	(0.400)

Note: We use alternative events, including national emergency declaration, first case in state, first death in state, and state shelter-in-place directive, to capture the outbreak of the pandemic. The event dummy equals 1 after each incident. The WFH and HPP indices are constructed using occupation attributes from O*NET, employment from OES, and individual data from the 2014-2018 5-year pooled ACS. The WFH/HPP dummy equals 1 if the WFH/HPP index is above the median. Daily social distancing and work behavior variables at county level are constructed from data provided by SafeGraph. Weekly unemployment data at state level come from the Department of Labor. In columns 1, 3 and 5, we control for state and weekday dummies. In columns 2, 4, 6 and 8, we control for the full set of regional covariates. All regressions are weighted OLS with county population (state population in the unemployment regressions) as weights. Standard errors are clustered at state level (no clustering in the unemployment regressions)and reported in parentheses. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.