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ABSTRACT

COVID-19, Stay-At-Home Orders and Employment: Evidence from CPS Data*

In this paper, we examine the short-term consequences of COVID-19 and evaluate the impacts of stay-at-home orders on employment and wages in the United States. Guided by a pre-analysis plan, we document that COVID-19 increased the unemployment rate, decreased hours of work and labor force participation, especially for younger workers, non-white, not married and less-educated workers. We built four indexes (exposure to disease, proximity to coworkers, work remotely and critical workers) to study the impact of COVID-19. We find that workers that can work remotely are significantly less likely to have their labor market outcomes affected, while workers working in proximity to coworkers are more affected. The unemployment effects are significantly larger for states that implemented stay-at-home orders. Our estimates suggest that, as of early May, these policies increased unemployment by nearly 4 percentage points, but reduced COVID-19 cases by 186,600– 311,000, and deaths by 17,851–23,325. We apply our estimates to compute lost income ($18.6–$21.4 billion), reduced government income tax revenues ($3.4–$5.5 billion), increased unemployment insurance benefit payments ($5–$5.8 billion) and reduced hospital costs ($0.7–$1.2 billion). Despite the jobs lost, age adjusted value of statistical life suggests that stay-at-home orders are cost effective.

JEL Classification: I15, I18, J21

Keywords: COVID-19, unemployment, wages, remote work, exposure to disease, essential workers, stay-at-home orders, lockdown

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The COVID-19 pandemic has had vast tragic human consequences. As of the end of April 2020, there were over 3,000,000 confirmed cases and about 210,000 fatalities worldwide. In addition from being a human tragedy, COVID-19 is also an economic tragedy. Evidence of the catastrophic impacts of COVID-19 is by now voluminous, with many modelling scenarios predicting a long recession.[1]

In this paper, we explore the short-term economic consequences of COVID-19 and stay-at-home orders on employment and wages in the United States. As of April 15, 2020 there were over 630,000 confirmed cases due to COVID-19 in the U.S. (Appendix Figure A1), with striking differences in the number of confirmed cases and deaths per capita across states (Appendix Figures A2 and A3). The central questions in this paper are: (1) What are the short-term impacts of COVID-19 on the labor market? (2) Are there larger effects for states with a greater number of COVID-19 cases and deaths? (3) Are there larger effects for specific occupations or occupation tasks? (4) What are the economic consequences of stay-at-home orders?

As a novel approach to transparency in economics, we exploit the fact that the post-COVID CPS (March) data was released only mid-April 2020, making it possible to pre-specify and publicly archive in a pre-analysis plan our analyses prior to obtaining the data.[2] Following our pre-analysis plan, we first investigate the impact of COVID-19 at the national-level using the Current Population Survey (CPS). Taken as a whole, we find that COVID-19 led to an increase of about 10 percentage point in the unemployment rate, a decrease of about 3.5 percentage points in the labor force participation and a small decrease in hours of work. We find that the labor market effects were larger for younger workers, not married, non-white and less-educated workers, and for states with relatively more confirmed cases and deaths per 10,000 inhabitants. These results suggest that COVID-19 may lead to an increase in labor market inequalities.[3]

Using a difference-in-difference framework, we estimate the effects of stay-at-

[1] A preliminary UN's Trade and Development Agency downside scenario expects a $2 trillion shortfall in global income (https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=2300).

[2] While using a pre-analysis plan is common practice now for lab and field experiments, it is less so in non-experimental settings. However, it has recently been shown that quasi-experimental studies suffer the most from p-hacking (Brodeur et al. (2018)). Our pre-analysis plan, see Beland, Brodeur and Wright (2020a), was archived on March 30, 2020, at https://osf.io/c28t5/. CPS data for the month of March 2020 were released mid-April 2020. We also added supplementary analyses in a second pre-analysis plan prior to the release of the April 2020 CPS data. In these analyses we investigate the impacts of government interventions on COVID-19 transmission and economic outcomes. Last, we follow Haushofer and Shapiro (2016) and report all modifications to the pre-analysis plan, and the reasons for them, in the Appendix 5.

[3] Many individuals were misclassified as "employed but not at work" instead of as "unemployed on layoff". We also estimate the impacts of COVID-19 for respondents who did not work and those who usually work full-time but did not in the reference week if a respondent was classified in either of the COVID-19 related explanations for their unemployment or reduced hours. See Section 3.

home orders on labor market outcomes and on COVID-19 case and death rates. Our results suggest that stay-at-home orders: increased unemployment by around 4 percentage points; reduced labor force participation by around 2.2 percentage points; and reduced COVID-19 cases and deaths per 10,000 individuals by 6–10 and 0.5–0.75, respectively.

We then investigate whether the economic consequences of this pandemic and of stay-at-home orders were larger for certain occupations and occupation tasks.[4] More precisely, we built four different indexes: workers relatively more exposed to disease, workers that work with proximity to coworkers, essential/critical workers and workers who can easily work remotely (See Section 2 for more details). Our estimates suggest that occupations that work in proximity to others have more adverse labor market outcomes during the pandemic and due to stay-at-home orders while occupations able to work remotely and essential workers are less affected.[5]

Lastly, we perform a back of the envelope calculations for the costs and benefits to date of the stay-at-home orders. Specifically we apply our estimates to compute lost income (\$18.6–\$21.4 billion), reduced government income tax revenues (\$3.4–\$5.5 billion), increased unemployment insurance benefit payments (\$5–\$5.8 billion) and reduced hospital costs (\$0.7–\$1.2 billion). We calculate that the orders lowered COVID-19 cases by 186,600–311,000 and deaths by 17,851–23,325. When combined with the estimates of cost, the implied value of statistical life is \$1.1–\$1.6 million which compares favorably to an age-adjusted value of \$4.4 million. Despite the jobs lost, our results suggest that stay-at-home orders are cost effective. Of note, our analysis and ability to fully detail the costs and benefits is limited. See Section 4 for a discussion.

We contribute to a growing literature on the economic consequences of COVID-19 (e.g., Alon et al. (2020); Atkeson (2020); Baek et al. (2020); Beland, Brodeur, Mikola and Wright (2020); Berger et al. (2020); Binder (Forthcoming); Couch et al. (2020); Engle et al. (2020); Kahn et al. (2020); Fetzer et al. (2020); Ramelli et al. (2020); Rojas et al. (2020)).[6] Our paper also adds to a large literature investigating the relationship between health and labor market outcomes (Currie and Madrian (1999); Strauss and Thomas (1998). Last, our work also relates to modeling of optimal mitigation policies during pandemics (e.g., Acemoglu et al. (2020); Jones et al. (2020)).[7]

[4]See the Appendix 5 for the results for each major occupational category.

[5]Kuchler et al. (2020) show that the spread of the disease is related to strength of social ties using Facebook data.

[6]See Allcott et al. (2020) and Baccini and Brodeur (2020) for the determinants of implementing stay-at-home orders.

[7]Our study also contributes to a large literature documenting the macroeconomic consequences of diseases and epidemics (Acemoglu and Johnson (2007); Ashraf et al. (2008); Barro et al. (2020); Bloom et al. (2014); Lorentzen et al. (2008)).

The rest of the paper is organized as follows. In Section 1, we provide background on the plausible channels through which COVID-19 and stay-at-home orders could affect labor market outcomes. Section 2 details the data collection and the identification strategy. We discuss the results in section 3. Section 4 is devoted to stay-at-home orders. Section 5 concludes.

1 Conceptual Framework

1.1 Channels

COVID-19 and government interventions, such as stay-at-home orders, aimed at reducing transmission may have negative consequences on the economy (Eichenbaum et al. (2020)).

A first channel through which COVID-19 may impact employment is destruction of human capital. As of April 18, 2020 deaths from COVID-19 stood at about 40,000 (Figure A1). It is thus plausible that COVID-19 cases and deaths will eventually affect the economy directly by affecting the labor supply of infected individuals. Note that labor market activity may be related to the health of other family members and friends (Berger and Fleisher (1984); Currie and Madrian (1999)).

Increased uncertainty and fear may also have an impact on consumer behavior (Hassan et al. (2020)).[8] Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020) show that the epidemic led consumers to initially increased consumption in specific sectors such as retail, credit card spending and food items, but that overall spending then decreased sharply. Similarly, increased uncertainty led to a very large decrease in consumer sentiment (Curtin (2020)), with plausibly larger decreases for states with more cases.[9]

1.2 Impact on Specific Occupations and Industries

Cancellations of trade shows, conventions and festivals, schools, daycare centers and other educational institutions will likely have a large negative impact on economic activity, especially for firms that require close physical proximity to other workers or clients (Koren and Pető (2020)). There is now growing evidence that a significant proportion of cases are related to occupational exposure, suggesting that certain occupations are now becoming riskier than others (Baker, Peckham and Seixas (2020)). In other words, occupational characteristics, such as interacting with the public and being in contact with other workers, may thus be correlated to the

[8] The pandemic may also cause political instability, which would translate into more uncertainty.

[9] Uncertainty may also change investment behavior. For instance, COVID-19 could affect the allocation of productive capital across countries.

likelihood of contracting the disease. We test throughout whether the economic impacts of the pandemic and stay-at-home orders are related to how 'risky' an occupation is. On the one hand, there may be a wage premium for workers in these occupations due to the sudden increase in risk (e.g., Smith (1979)). On the other hand, some workers might decide to stop working (or forced to) given the increasing risk (Garen (1988)). These two forces could lead to a decrease in the likelihood to work, but an increase in wages for workers who still work.

Stay-at-home orders could also have an effect on the economy through mandated closure of "non-essential" industries. While the list of essential employees varies across locations, the list of essential workers typically include the following: medical and healthcare, telecommunications, information technology systems, defense, food and agriculture, transportation and logistics, energy, water and wastewater, law enforcement, and public works industries. Essential workers, and especially those in risky occupations, could be those who are compensated for the increase in risk. The pandemic could also lead to an increase in demand for health care workers to help face the crisis.

Another dimension that we test is whether occupations with relatively more workers working remotely pre-COVID-19 were less impacted. The COVID-19 outbreak and government interventions are forcing an increasingly large number of workers to work from home. In states without regulations, many companies are encouraging or mandating that staff adopt a work-from-home policy. While these government and company policies are easily applicable in many industries, it is less the case for others. For instance, the infrastructure and policy needed for remote working for high tech firms were already in place, making the adoption of such policies feasible.

Last, COVID-19 may have been beneficial to some industries, such as consumer packaged goods and heath care, because of an increase in demand. Recent reports suggest that grocery stores, drug stores and delivery companies are seeking to fill hundreds of thousands of positions because of the panic and stay-home orders. For instance, Amazon has pledged to open 100,000 new full-time and part-time positions to meet the surge in demand and to increase pay by $2/hour (Amazon Blog (2020)). We confirm that some occupations suffered less from COVID-19 in the Appendix 5.

2 Data and Identification Strategy

In this section, we describe our data sets and detail our specification and controls, which were pre-specified in a pre-analysis plan.

2.1 COVID-19

Data at the national-level is reported and updated by the CDC on a regular basis.[10] Unfortunately, the CDC is not currently publishing disaggregated data at the day- or week-level for each state. For this project, we rely on data from the COVID Tracking Project (https://covidtracking.com/). The database is the product of important data collection efforts relying on information from state public health authorities, or, occasionally trusted media articles and news conferences.

Appendix Table A1 shows the dates of the first confirmed case (column 1) and death (column 2) for each state.[11] Only Vermont and West Virginia had not announced a confirmed case by March 14, 2020, the last day March CPS respondents were interviewed. All states had at least one confirmed case and one death by April 18, 2020, the last day April CPS respondents were interviewed.[12]

Note that there could be measurement error in the date that new cases are confirmed. For example, some states may publicly report new confirmed cases on a specific date, but could have actually confirmed the case the previous day. We think this is not an issue given that our analysis is at the month-level and the fact that we are interested in the economic impacts of known, confirmed cases.

In our sample, which corresponds to the last day of the week for which employment information is collected by the CPS (February–April 2020), the average cumulative number of confirmed cases per 10,000 is 3.99 (std. dev. 10.98), while the average cumulative number of deaths per 10,000 inhabitants is 0.140 (std. dev. 0.471).[13]

2.2 Current Population Survey

We match our COVID-19 data with the Current Population Survey (CPS) from Integrated Public Use Micro Samples (IPUMS). The CPS is conducted by the Bureau of Labor Statistics (BLS) and is a monthly survey of 60,000 eligible households. The CPS provides a large sample size of workers and individual characteristics such as age, education, race, and marital status and labor market characteristics such as labor force participation, employment status, hours of work, occupation and industry. The survey questions refer to activities during the week that includes the 12th of the month.

[10] See https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html for the national data.

[11] Appendix Figures A4 and A5 illustrate the number of states with at least one confirmed case and at least one death over time, respectively.

[12] Appendix Figure A6 provides a timeline of the pandemic for the U.S.

[13] Appendix Figures A7 and A8 illustrate the geographical distribution of COVID-19 cases and deaths as of April 18, 2020, while Appendix Figures A9 and A10 show cases and deaths as of March 15, 2020.

The CPS typically includes both in-person and telephone interviews. In our pre-COVID-19 sample, about 51% were collected over the phone. Unfortunately, COVID-19 had an impact on data collection. For March and April 2020, only telephone interviews were conducted and two call centers were closed. The response rate (73% in March and 70% in April) was therefore about 10–13 percentage points lower than in preceding months (U.S. Bureau of Labor Statistics (2020)). Of note the response rate for households entering the sample was particularly low. Nonetheless, the BLS "was still able to obtain estimates that met [their] standards for accuracy and reliability" (U.S. Bureau of Labor Statistics (2020)). In the empirical analysis, we control for whether the interview was done in-person or telephone.

Table 1 provides descriptive statistics for our labor market outcome variables of interest from January 2016 to April 2020. Our sample consists of civilians aged 16–70 over the time period. We have 3,070,317 observations for unemployment. Our sample size is smaller for hourly wages since this information is only asked of the outgoing rotation groups. Approximately 4.4% of respondents were unemployed and 71% were in the labor force. We restrict the sample to individuals working for hours of work and wages. On average, the real hourly wage (2018 dollars) was about $18 and workers were usually working 39 hours per week at all jobs.

2.3 Occupational Measures of Exposure, Remote Work and Essential Workers

Our occupational measures of exposure to disease or infection and physical proximity come from the Occupational Information Network (O*NET) survey data. O*NET is a program sponsored by the U.S. Department of Labor which aims to gather occupational data and develop applications to help create and maintain a skilled labor force. The survey data is collected after pre-testing survey construction and features done in conjunction with the Department of Labor. The survey uses a two-stage design. First, businesses expected to have the occupations required are randomly sampled and then workers from those business are randomly sampled and provided questionnaires.

Our measure of exposure to disease is taken from a survey question asking "How often does this job require exposure to disease/infections?" with five possible answers: (1) Never, (2) Once a year or more but not every month, (3) Once a month or more but not every week, (4) Once a week or more but not every day, and (5) Every day. The translation of these responses into an index is done by O*NET and shown in Appendix Figure A11.[14] The top and bottom 15 occupations are shown in Appendix Table A2. The following four occupation codes have a score of 100: Acute

[14]The exact formula used for converting the survey responses into the index values is described in the Appendix.

care nurses, dental hygienists, family and general practitioners, and internists.

Our measure of physical proximity is taken from a survey question asking "How physically close to other people are you when you perform your current job?" with five possible responses: (1) I don't work near other people (beyond 100 ft.), (2) I work with others but not closely(e.g., private office), (3) Slightly close (e.g., shared office), (4) Moderately close (at arm's length), and (5) Very close (near touching). The analogous graphic for this question is shown in Appendix Figure A12. The top and bottom 15 occupations are shown in Appendix Table A3. The following four occupation codes have a score of 100: Choreographers, dental hygienists, physical therapists, and sports medicine physicians.

We convert the O*NET occupation codes into Standard Occupational Classification (SOC) codes using the crosswalks provided by O*NET.

We complement these indexes by using the classifications of the feasibility of working from home created by Dingel and Neiman (2020) and essential worker designations based on the LMI Institute index.[15][16] The essential workers index provides a list of essential occupations in several fields: medical and healthcare, telecommunications, information technology systems, defense, food and agriculture, transportation and logistics, energy, water and wastewater, law enforcement, and public works industries.

We then merge these indexes with our data from the CPS after converting its occupation codes into SOC equivalents. In cases where the SOC codes from the CPS are at a higher level of aggregation than those of our indexes, we assign an index value based on the weighted average of the sub-occupations, weighting by each sub-occupation's share of employment in the aggregated occupation (taken from the BLS' Occupational Employment Statistics estimates). Table 1 provides descriptive statistics. Indexes are standardized to a mean of 0 and standard deviation of 1, to facilitate interpretation (numbers will not be exactly 0 or 1 due to rounding). Our exposure and proximity indexes take on a much wider range of values, in part because the classifications that our remote and essential worker indexes are built from are binary (except where occupations are at a higher level of aggregation).

Figure 1 illustrates three of our indexes. Each circle in the figure represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's physical prox-

[15] See this link for more details: https://www.lmiontheweb.org/more-than-half-of-u-s-workers-in-critical-occupations-in-the-fight-against-covid-19/.

[16] Dingel and Neiman (2020) classify the feasibility of working at home in the U.S. and argue that 34% of jobs can plausibly be performed at home. Brynjolfsson et al. (2020) conducted a survey early April and found that 34% of individuals employed four weeks earlier reported they were commuting and are now working from home.

imity to coworkers, measured by O*NET's index. The further to the right, the closer in proximity employees in that occupation work with their coworkers. The y-axis plots each occupation's exposure to infection and disease, also measured by O*NET's index. The further up, the more frequently employees in that occupation are exposed to infection and disease. The color of the circles corresponds to whether or not an occupation can be done remotely. For simplicity, in this figure we code any occupation as "can be done remotely" if the share of jobs that can be done in that occupation is greater than zero.[17]

We can see a clear positive (convex) relationship between our indexes of physical proximity and exposure to infection and disease, with health workers (e.g., dentists, nurses and physicians) scoring relatively high for both indexes. The correlation between exposure and proximity is 0.589. In contrast, there is a negative correlation between remote work and exposure (correlation of -0.197), suggesting that workers in occupations requiring exposure to disease/infections are less likely to be working from home. Similarly, our remote work and proximity indexes are negatively correlated (correlation of -0.463). Our essential workers index is negatively correlated with remote work (-0.149) while being positively correlated with our exposure index (0.0124) and mildly negative correlated with our proximity to coworkers index (-0.001).

2.4 Identification Strategy: National and State-Level

We first rely on a simple pre/post analysis at the national-level. The model is:

$$Y_{i,s,t} = \alpha + \beta PostCOVID_t + X'_{i,s,t}\gamma + \theta_s + \delta_t + \varepsilon_{i,s,t}, \tag{1}$$

where $Y_{i,s,t}$ is an economic outcome for individual i in state s and month t. Our four main outcomes variables are the (1) unemployment rate, (2) labor force participation, (3) hours of work, and (4) hourly wages. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Hours of work are computed for civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Hours of work is trimmed to exclude values below 1st percentile and above 99th percentile. The hourly wages (in 2018 constant dollars) is computed for civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. It excludes self-employed persons and we trim to exclude values below 1st percentile and above 99th percentile.

$Post\ COVID_t$ is an indicator equals to one for March and April 2020 and zero

[17] We also present variants of this in Appendix Figures A13 and A14.

for all preceding months. The time period is January 2016 to April 2020. $X_{i,s,t}$ is a vector of other regressors including age, gender, marital status and race. Finally, θ_s and δ_t represent state and time fixed effects, respectively.

We also control for demographic characteristics, the educational level of the respondent and interview type fixed effects, i.e., telephone or in-person. Moreover, to allow for common regional shocks to a given economic outcome, we include interactions between year fixed effects and the four Census regions. We report standard errors clustered at the state-level.

2.5 Identification Strategy: Stay-at-Home Orders

In order to estimate the impacts of stay-at-home orders we use a differences-in-differences strategy, comparing states that implemented these policies to those that did not. As a robustness check, we also estimate the effect of stay-at-home orders on labor market outcomes and COVID-19 known cases using synthetic control method. The methodology and results are presented in the Appendix 5.

The date of announcement and date of implementation of stay-at-home orders come from the New York Times and other local newspapers sources.[18] The differences-in-differences model is:

$$Y_{s,t} = \alpha + \beta STAYHOME_{s,t} + X'_{s,t}\gamma + \theta_s + \delta_t + \varepsilon_{s,t}, \tag{2}$$

where $Y_{s,t}$ is either one of four economic outcomes — unemployment rate, labor force participation rate, hours worked, and hourly wage — or COVID-19 known cases (or deaths) per 10,000 inhabitants in state s and month t. The time period is January 2016 to April 2020. $STAY\ HOME_{s,t}$ is equal to one if the state had announced a stay-at-home order in time t.[19]

$X_{s,t}$ is a vector of other regressors including the number of COVID-19 tests performed per 10,000 inhabitants. This control is added to the model as some states were able to perform tests earlier than others or were more proactive at testing.

Finally, θ_s and δ_t represent state and month $\times$ year fixed effects, respectively. For specifications estimating the effect on cases per 10,000 individuals, which are at the daily-level, we also include day of week and state-specific time trends. We weight our results by state population and report standard errors clustered at the state-level. We follow Hsiang et al. (2020) and exclude Connecticut and North Carolina due to concerns about their testing rates.[20]

[18] See https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html.

[19] Typically, the announcement precedes the date of implementation by two or three days.

[20] Our differences-in-differences estimates are robust to their inclusion, providing nearly identical

3 Short Run Economic Consequences

In this section, we describe the relationship between COVID-19 and employment status, with a particular focus on our four indexes. We first test this relationship at the national-level, and then explore whether the economic impacts were larger in states with relatively more cases and deaths per capita.

3.1 National-Level: Employment, Hours of Work and Wages

We begin our analysis with a graphical representation of the effect of COVID-19 on our four main labor market outcomes. Figure 2 displays the unemployment rate (Panel (a)), labor force participation (Panel (b)), hours of work (Panel (c)) and hourly wages (Panel (d)) over the time period January 2016 to April 2020. Looking at these figures, we observe a visible increase in the unemployment rate in March 2020, and a drastic increase in April 2020, suggesting very large effects of COVID-19 on the U.S. labor market. More precisely, the unemployment rate increased by about 0.9 percentage points from February to March 2020 and by more than 9 percentage points from March to April 2020, reaching more than 14 percent. The unemployment rate had not been this high since the Great Depression. Similarly, there was a decrease in labor force participation of about 3.5 percentage points from February to April 2020. For hours of work, workers experienced a small drop of approximately 0.75 hours. Interestingly, real hourly wages increased in April by more than $1, possibly due to the strong compositional changes in the labor force.

Table 2 - column 1 presents our regression analysis. This table contains OLS estimates of equation (1) for our four outcome variables. The time period is January 2016 to April 2020. The dependent variables are respectively the unemployment rate (Panel (a)), labor force participation (Panel (b)), hours of work (Panel (c)) and hourly wages (Panel (d)). We report standard errors clustered by state.

What clearly emerges is that following COVID-19, there is a substantial increase in the unemployment rate, a decrease in labor force participation and a decrease in hours of work. The estimates are all statistically significant at the 1 percent level. In contrast, the estimates for hourly wages are positive. Our findings are thus in line with many studies documenting that health has greater effects on hours of work than on wages (e.g., Currie and Madrian (1999); Wolfe and Hill (1995)).

For the CPS March and April 2020, respondents who did not work during the reference week were asked a follow-up question inquiring about the reason for not working. Those who indicated they did not work because they were ill, self-isolating due to health concerned, or were under quarantine were coded as not working due to "own illness, injury, or medical problem" while those who were not ill or quarantined

point estimates.

but were not working as a result of the coronavirus were coded as "on layoff" (either temporary or indefinite). If the respondent was uncertain of their return to work within 6 months (the threshold for temporary layoff) interviewers were advised to include them as temporary layoffs.

Respondents who usually worked full-time hours (35 or more) but answered between 1 and 34 hours in the reference week were also asked a follow-up question inquiring about the reason for the change in hours. Those who indicated they did not work because of illness, self-isolation, or quarantine were coded as not working full-time due to "own illness, injury, or medical problem" while those whose hours were reduced for non-illness or quarantine reasons were classified as "slack work or business conditions".

Despite the guidance given to interviewers, the BLS admitted that some people were misclassified as "employed but not at work" instead of as "unemployed on layoff".[21] This misclassification biases our estimates for unemployment effects downwards. A back of the envelope calculation treating all workers above the March average from 2016–2019 who have the "other reasons" explanation for work absence as unemployed (about 1.4 million people) results in an approximately 0.9 percentage point increase in the unemployment rate over the 'officially' reported figure. Attempts at reclassifying individuals would require assumptions about who exactly was misclassified, assumptions that could introduce large measurement error for subgroup analysis.

Based on the classification scheme and guidance provided by the BLS, we estimate equation (1) for those who did not work, who were employed but absent, and those who usually work full-time but did not in the reference week. These results are presented in Table 3 - column 1. Panel (a) presents the results for COVID-19 related explanations of unemployment and the dependent variable is a dummy that equals 1 if an unemployed individual is coded as being unemployed either due to "own illness, injury, or medical problem" or "on layoff". We find that these explanations are approximately 50 percentage points more likely in March-April 2020. Panel (b) provides the estimates of explanations for individuals working part-time instead of their usual full-time hours and the dependent variable is a dummy that equals 1 if the explanation for reduced hours is either "own illness, injury, or medical problem" or "slack work or business conditions". Our estimates suggest the COVID-19 related explanations are nearly 14 percentage points more likely in March-April. Panel (c) contains estimates for the explanations of work absences and the dependent variable

[21] In March 2020 there were 6.4 million people classified as employed but not at work, with 2.1 million of these being classified as "other reasons" (non vacation, illness, family obligation, weather, childcare issues, civic/military duty, school, parental leave). The average of estimates for this category from 2016–2019 is roughly 700,000. The BLS explains that they will not attempt to reclassify individuals who were incorrectly coded (U.S. Bureau of Labor Statistics (2020)).

is a dummy that equals one if the explanation for being absent is "other reasons". This COVID-19 related explanation is about 41 percentage points more likely in March-April. These results are statistically significant at the 1% level and suggest that using the unemployment rate as a dependent variable leads to underestimating the economic impacts of COVID-19.

3.2 National-Level: Socioeconomic Groups

We now investigate with graphical representations the short-term effects of COVID-19 on labor market outcomes for different subgroups of respondents. Appendix Figures A15-A20 illustrate our outcome variables by gender, age groups, marital status, race, educational attainment and immigration status, respectively. The structure is the same as in Figure 2. We describe each figure at length in the Appendix 5. Overall, we find that all subgroups experience an increase in unemployment, but with strong heterogeneity; younger, not married, less educated and immigrant workers are relatively more negatively affected by the pandemic. We also find that all race groups are negatively affected by COVID-19 but the decline in labor market outcomes seems larger for Asians, Blacks, and Hispanics, compared to Whites.[22]

Appendix Tables A4, A5, A6 and A7 confirm these patterns. We interact our variable of interest, $Post\ COVID$, with a dummy for male respondents in column 1, dummies for the age categories 16–34 and 35–54 in column 2, a dummy for being married in column 3, and our four race dummies in column 4, respectively. White being the omitted category. We find that women are more likely to be unemployed as a result of the pandemic but that men are more likely to exit the labor force and the large decline in wages suggests those exiting have lower wages. We also find that COVID-19 has larger effects on younger workers' (aged 16 to 34) unemployment and labor force participation. Moreover, these tables find smaller negative effects of COVID-19 for married individuals for unemployment and labor force participation. We also find that that Hispanics, Asians, and other Non-whites are significantly more likely to be unemployed due to COVID-19 than Whites. We also find that labor force participation for Blacks is significantly more negatively affected than Whites. Overall, these results suggest an increase in labor market inequalities.

3.2.1 National-Level: Occupational Tasks We now explore whether COVID-19, as of April 2020, had larger impacts on workers relatively more exposed to disease, working in proximity to coworkers, who can easily work remotely and essential

[22] This result is consistent with Hispanics being more concerned about the threat the COVID-19 outbreak poses to their financial situation and the day-to-day life of their local community (Pew Research Center (2020)).

workers.[23]

Figure 3 graphs the labor market outcomes for workers above and below the median of our exposure to disease and infections index. This figure suggests that workers in occupations with above median exposure experienced a more pronounced increase (decline) in unemployment rate (labor force participation) than those workers in below median exposure occupations, but both groups suffered drastically. Individuals in both groups seem to experience small decreases in hours of work and increases in hourly wages. While some workers who would have been more exposed to COVID-19 received pay increases, it is more likely that the increase in wages stems from job losses being concentrated among those with lower wages.

Figure 4 plots the labor market outcomes for individuals above and below the median values of our proximity to coworkers index. Those who work in occupations above the median value seemingly had a much larger increase (decrease) in unemployment (labor force participation) in March and April 2020. The figure also suggest a wage increase for workers working in proximity to others. This perhaps suggests that it was low wage workers in the above median group that transitioned into unemployment.

Figure 5 shows the split for individuals in occupations classified as those that can and cannot be done remotely. The figure shows that both workers who can and cannot work remotely saw an increase (decrease) in unemployment (labor force participation), but that those able to work remotely were less affected in both categories.

Figure 6 presents results for workers classified as essential or non-essential. The figure suggests larger negative effects for unemployment and labor force participation for non-essential workers.

In columns 2-5 of Table 2, we formally test whether COVID-19 had different impacts on our subgroups of workers for our four labor market outcomes of interest. All columns include our usual set of fixed effects and demographic controls and include $Post\ COVID$, $Index$ and the interaction of these two variables. $Index$ corresponds to one of our four indexes (exposure, proximity, remote work and essential workers). Column 2 presents our measure of exposure, column 3 presents our measure of proximity, column 4 our measure of remote work and column 5 our measure of essential workers.

In column 2 of Table 2, we find that workers relatively more exposed to disease are not significantly more likely to be affected by COVID-19. The point estimates for the interaction terms ($Index \times PostCOVID$) are not statistically significant

[23] In Appendix Figures A21–A42 we also plot monthly unemployment, labor force participation, hourly wages, and hours worked for each major occupational category. We describe the results in the Appendix 5.

for unemployed, labor force participation, hours of work and hourly wages.

In column 3 of Table 2, we find that workers relatively working more in proximity to coworkers are more likely to be unemployed and less likely to be in the labor force. The coefficients are statistically significant at the 1% level. Moreover, we find that these workers are more likely to have higher hourly wages, which again suggests a change in the composition of workers.

In column 4 of Table 2, we find that workers relatively more able to work remotely are significantly less likely to be unemployed and more likely to be in the labor force. The effect is significant at the 1% level. There is no significant impact on wages and hours worked.

In column 5 of Table 2, we investigate the labor market outcomes of essential workers. We find that essential workers are significantly less likely to be unemployed. However, we find a significant decrease in hours worked.

In columns 2-5 of Table 3, we study COVID-19 related absences, using our indexes. In sum, we find that all group of workers see an increase in unemployment, reduced hours and absences from work due to COVID-19. However, we find heterogeneity across our indexes. We find that workers able to work remotely are significantly less likely to report COVID-19 unemployment and absences. In contrast, workers working in proximity to others are significantly more likely to report COVID-19 unemployment and absences, and workers with more exposure are more likely to report COVID-19 related unemployment and absences. The interaction term is not statistically significant for essential workers.[24]

3.3 Employment and Wages: State-Level Cases and Deaths

Appendix Figure A43 plots our labor market outcomes for individuals split by states with cumulative known COVID-19 case rates above and below the median. We find that states above the median case rate experienced a larger increase in unemployment and a larger decrease in labor force participation. Looking more specifically at the change from February 2020 to April 2020, states with above median case rates saw an 11 percentage points increase in unemployment against 8.5 percentage points for states below the median. The difference in hours worked per week is also more pronounced for the states above the median.

[24]We also analyze the impacts of COVID-19 on self-employed workers in Appendix Figure A44. The figure separates between incorporated and unincorporated. There are two groups of self-employed workers in the CPS: incorporated (working for themselves in corporate entities) and unincorporated (working for themselves in other entities).The literature argues that incorporated entities is a better proxy for entrepreneurship (e.g., Levine and Rubinstein (2017); Beland and Unel (2019)). Appendix Figure A44 shows that the negative impacts of COVID-19 on labor market outcomes is present for both incorporated and unincorporated entities and the effect is important for hours worked. Therefore, our results suggest that COVID-19 has a negative impact on entrepreneurship activities.

We confirm these results in Table 4. The variables of interest are the number of cumulative COVID-19 cases (columns 1, 2, 5 and 6) and deaths (columns 3, 4, 7 and 8) per 10,000 inhabitants.[25] We find that the cumulative number of cases and deaths at the state-level is positively associated to the unemployment rate and negatively related to labor force participation and hours of work, confirming that individuals in states with more COVID-19 cases were more affected. The estimates for unemployment are statistically significant, and suggest that an increase of 10 known cases per 10,000 inhabitants is associated with an increase in the unemployment rate of nearly 2 percentage points. The estimates for wages are positive, and significant, suggesting once again changes in the composition of workers.

3.3.1 Impacts by Occupation: State-Level cases

Appendix Tables A8 - A11 provide estimates for the differential effects of COVID-19 on workers across our exposure, proximity, essential workers and remote work indexes using the cumulative known COVID-19 cases or deaths per 10,000 inhabitants, instead of *Post COVID*. We find that occupations that work in proximity to others are more likely to be unemployed due to COVID-19. We also find that workers in occupations that can work remotely are less likely to be unemployed and work more hours. The effects are significant at the 1% level. These results are in line with our national-level analysis. We also find that in states with larger deaths per capita, essential workers are less likely to be unemployed.[26]

4 Government Response: Stay-at-Home Orders

This section first discusses the plausible effects of state stay-at-home orders on labor market outcomes and COVID-19 known cases using a differences-in-differences framework.[27] We then provide back of the envelope calculations of the labor market outcomes externalities generated by these orders.

4.1 Stay-at-Home Orders: Labor Market Outcomes

The evidence has so far suggested that stay-at-home orders (or lockdowns) is one of only a few instruments available to halt the spread of COVID-19, absent a vaccine. Unfortunately, these government policies may come at a large economic cost.

[25] We also include the number of cumulative COVID-19 cases and deaths per 10,000 inhabitants squared. We find a a negative coefficient on the squared term and a positive coefficient on the coefficient for unemployment, suggesting that layoffs are slowing down for each new case or death.

[26] Appendix Tables A12 - A15 present heterogeneity results using the cumulative known COVID-19 cases as the explanatory variable. We find once again heterogeneity in the effect of COVID-19: younger and Non-white workers are more likely to have negative labor market outcomes due to COVID-19.

[27] See Appendix 5 for our synthetic control method estimates.

We estimate the effect of these policies using first a traditional differences-in-differences framework. Table 5 Panel A, shows estimates of equation 2, and tests whether states that implemented stay-at-home orders as of April 11, 2020 (end of the week that questions are referred to in the CPS) had worse labor market outcomes, conditional on the number of COVID-19 tests performed.

Our differences-in-differences estimates suggest that states who had implemented stay-at-home orders saw a higher unemployment rate and a lower labor force participation rate. The estimates for unemployment and labor force participation are statistically significant at conventional levels, and suggest stay-at-home orders increased the unemployment rate by 3.8 percentage points and decreased the labor force participation by 2.5 percentage points. In contrast, we do not find evidence that stay-at-home orders affected hourly wages and hours of work.

Figure 7 presents the event-study estimates of the leads and lags of our treatment variable. The estimates plotted in this figure are in line with the results presented in Table 5. Unemployment increased and labor force participation decreased in states that implemented a stay-at-home order in comparison to states that did not by about 4 and 2 percentage points, respectively, in April 2020. On the other hand, the estimates for the months before the implementation of stay-at-home orders are much smaller and statistically insignificant. No clear patterns emerge for our two other outcomes.

Appendix Tables A16-A19 explore heterogeneity effects of stay-at-home orders by gender, marital status, age, race and education. We find that the estimated effects of state orders for unemployment are significantly larger for women, younger, not married, Hispanic and less educated workers. The estimates for labor force participation are in line with the unemployment results. We do not find large differences across socioeconomic groups for hours of work except for women who report working significantly more after the policy.

In Appendix Tables A20-A23, we also explore the impacts of stay-at-home orders using our indexes. We find that stay-at-home orders have larger effects on workers in close proximity to coworkers, and smaller effects on critical workers and workers who can more easily work remotely.

We also explore whether part of the effect of stay-at-home orders is due to social distancing. A number of studies document that stay-at-home orders decreased non-essential visits and distance traveled (e.g., Engle et al. (2020)). For this exercise, we extract cell phone data from Unacast's COVID-19 Toolkit. (This analysis was not included in our pre-analysis plan.) Unacast provides indexes evaluating the effectiveness of social distancing using cell phone data. The data can be visualized here: `https://www.unacast.com/covid19/social-distancing-scoreboard`. Three different metrics are computed: the percent change in average distance travelled, the percent change in "non-essential visitation", and the change in "human encounters". Non-essential visits include, for instance, travels to venues like spas, cinemas, and clothing stores. In Table 6, we examine how stay-at-home policies, conditional on these three measures of social distancing, affect our four labor market outcomes. The analysis is for the time period February to April 2020. For this time period, our estimates suggest that stay-at-home orders increased the unemployment rate and decreased labor force participation by 3.8 and 2.2. percentage points, respectively. Controlling for our three indexes decrease the size of our statewide policy variable (in absolute term) by about 30% for unemployment and labor force participation, suggesting that decreasing demand played an important role in the increase in unemployment.

4.2 Stay-at-Home Orders: COVID-19 Prevention

We now explore whether the implementation of stay-at-home orders reduce transmission of COVID-19. A growing number of studies have investigated the effect of lockdowns on COVID-19 known cases and deaths in China and Europe (e.g., Fang et al. (2020); Ferguson et al. (2020); Hartl et al. (2020)). For the U.S., Hsiang et al. (2020) estimate that there would be approximately 5.1 million more cumulative confirmed cases without the implementation of anti-contagion policies, while Greenstone and Nigam (2020) argue that moderate social distancing could save over 1.5 million lives between March 1 and October 1, with over 600,000 due to avoided overwhelming of hospital intensive care units. In what follows, we estimate the effect of stay-at-home orders on COVID-19 known cases and deaths as of the beginning of May, 2020.

Figure 7 provides event-study estimates of leads and lags, with Panels E and F containing daily estimates of cases and deaths per 10,000 inhabitants, respectively. The leads and lags allow to test whether the effect is intensifying over time. There does not appear to be a change in the estimated effect of the policy prior to the policy's announcement, providing suggestive evidence in favor of our identifying assumption. Perhaps reassuringly, we see a relatively muted effect of the policies in the immediate aftermath of their announcement and it is only after about 10 days that we see a sizeable drop in the point estimates. This is reassuring given that the effects do not appear sooner than one incubation cycle of the virus and corresponds quite well to the estimated 11 day window of symptom development (Lauer et al. (2020)). These figures suggest that after that first symptom development cycle, states who implemented the orders are seeing 10 fewer cases per 10,000 inhabitants and nearly 1 fewer death per 10,000 inhabitants.

Table 5 Panel B, presents the effect of stay-at-home orders on COVID-19 cases and deaths rate per 10,000 inhabitants, using our differences-in-differences estimations. Columns 1–2 provide results using the entire post-order period while columns 3–4 exclude the first 11 days corresponding to the incubation period of the virus. Our estimates in columns 1–2 being much lower than those in columns 3–4 corroborate the event-study findings of a muted effect during the first post-treatment incubation period with a much larger effect afterwards. We find that post-incubation period, states with stay-at-home orders saw 6 fewer cases and 0.57 fewer deaths per 10,000 inhabitants, on average.

4.3 Stay-at-Home Orders: Back of the Envelope

In this subsection, we provide back of the envelope calculations of the labor market externalities generated by stay-at-home orders.

It is important to note that in what follows we assume our estimated effect sizes for stay-at-home orders are constant and that our estimates of cases (and therefore deaths) are as of the beginning of May, 2020. As these effects could exhibit heterogeneity over time (e.g., evolving non-linearly) we could be underestimating both the costs of the labor market effects and the COVID-19 prevention effects. Moreover, our back of the envelope calculations will obviously not be integrating all the economic costs associated with stay-at-home orders.

Our differences-in-differences and lead/lag estimates suggest an average increase in the monthly unemployment rate of 3.5–4 percentage points as a result of the stay-at-home orders. The unemployment rate in April for states with orders was 14.8 percent, suggesting a counterfactual 10.8–11.3 percent in the absence of the policies that corresponds to 5.2–6 million additional jobs lost. Recall that the BLS estimates that an additional 1.4 million workers could have been misclassified as "employed, but absent" rather than "unemployed, temporarily laid off", so our numbers are underestimates.

We predict the wage of individuals who were likely to lose their job because of the lockdown. More precisely, we rely on our results on the heterogeneous effects of the lockdown seen in Appendix Tables A20-A23.[28] Our point estimates of the wage rate and hours are not statistically different than zero. We observe that our predicted wage rate and hours worked in April for states with orders are \$17.8 and 37.8 hours if we multiply the wage rate and hours worked, scale to the average number of weeks under the policy (5.3) and multiply through by the number of jobs lost, we obtain estimates of lost income (albeit with assumptions). We therefore

[28] The estimated wage used in this approach is approximately \$1.5 dollars lower than the average wage of workers in treated states after the orders are implemented. This is due to certain groups (e.g., women, Hispanic people) earning less while being more likely to lose their jobs as a result of the policies.

estimate lost income to range between \$18.6–\$21.4 billion as of early May.

In terms of foregone tax revenue as a result of the policies, we assume that those who become unemployed earn an average wage of \$17.8, the value suggested by our estimates above, and calculate their tax bracket by multiplying this wage rate by our estimated weekly hours (37.8) and full year weeks (50). This yields an average income of \$33,642. The average annual state tax among those with policies for a single filer at this income level is \$933.24, which when scaled to the duration of stay-at-home orders thus far becomes \$95.12.[29] If we multiply this by the number of unemployed in the affected states we get a total forgone tax revenue of \$494–\$570 million to date, under the assumption that these individuals remain in the same tax bracket over the course of the year. The annual federal income tax associated with that income level is \$2,379 (\$242.48 when scaled to average policy duration), a similar calculation returns foregone income tax revenue of \$1.2–\$1.4 billion thus far with the federal government losing a nearly identical \$1.3-\$1.5 billion in FICA funding which goes towards Social Security and Medicare.

We now calculate the cost from additional unemployment benefits claim due to the stay-at-home orders. Importantly, we are not considering the full price of stimulus packages likes the Coronavirus Aid, Relief, and Economic Security (CARES) Act. As the CARES Act provides federal funding for unemployment benefits until the end of the calendar year, these costs will necessarily accrue to the federal government. The average UI state benefit in March 2020 was \$378 per week and the CARES Act provides an additional \$600 per week, for a total of \$978 per week. Multiplying this by our estimated unemployment and then by the 5.3 weeks of average policy duration to this point, we obtain estimates of \$5–\$5.8 billion in additional unemployment insurance benefits from stay-at-home orders.

We also estimate an average decrease in the case rate of 6 cases per 10,000 individuals after one incubation cycle (Table 5). The April case rate for states issuing orders was 25 cases per 10,000, suggesting an alternative case rate of 31 in the absence of orders which corresponds to 186,600 fewer cases (when scaled by population of these states). We use our post-incubation period estimate of -0.574 for deaths per 10,000 inhabitants to calculate the number of deaths avoided. The death rate per 10,000 inhabitants in April for states with orders was 0.993 per 10,000 suggesting an alternative death rate of 1.567 in the absence of the orders and 17,851 deaths avoided. This estimate is likely a lower bound as our sample period ends and it is likely that some COVID-19 cases will result in additional deaths. If instead we use the estimates of case (10 fewer cases) and death (0.75 fewer deaths)

[29] We use an online state-level tax calculator (https://www.smartasset.com) and as these individuals predominantly come from the low end of the income distribution we do not include 401k or IRA deductions. Nor do we include any additional deductions beyond the state personal deduction.

reduction from the midpoint of the post-incubation Figure 7, we obtain calculations of 311,000 fewer cases and 23,325 fewer deaths.

In order to provide a rough estimation of the change in burden on healthcare as a result of stay-at-home orders, we multiply the ratio of hospitalization to cases in states with stay-at-home orders (0.125) by our case reductions from above. This implies a reduction of 23,250 hospitalizations. Recent estimates of the cost of hospitalization for COVID-19 could be as high $30,000 per patient, suggesting an avoided healthcare burden of $700 million.[30] The corresponding reduction in hospitalizations from the leads and lags figures is 38,875 valued at $1.2 billion. We echo the caution in the use of hospitalizations data provided by The COVID Tracking Project (our main data source for COVID-19 data), who indicate that reporting of these measures is sparse and their use should be with caution for national summaries.

Combining the foregone income, increased unemployment insurance benefit payments, and reduced government taxes with our reduced deaths estimates (both from Table 5 and Figure 7), the implied cost per life saved falls between $1.1–$1.6 million. Even if we were to include all 1.4 million of the BLS' estimated misclassified workers as coming from treated states, the implied cost per life becomes $2 million. When comparing this to contemporary guidance issued by the U.S. government on the value of statistical life (VSL), which ranges from $6 to $13.9 million (2020 dollars) it would appear these policies are quite cost efficient.[31] However, as noted by Greenstone and Nigam (2020), taking account of the heterogeneous impacts across age groups has large implications for VSL calculations as most of the benefits of avoided fatalities are concentrated among the elderly. Using the age adjusted VSL from Murphy and Topel (2006) suggests the appropriate comparison for our estimated benefits is $4.4 million.

It is important to stress that these back of the envelope calculations are limited in their ability to fully detail the costs and benefits. For example, we are unable to account for long-term damage to quality of life stemming from the virus (e.g., Chen et al. (2017)) and do not consider other externalities such as impacts on crime, mental health, or the environment.

5 Conclusion

We study here the relationship between COVID-19, stay-at-home orders and the labor market in the U.S. Using data on COVID-19 cases and deaths, and data from

[30]Estimates taken from a report from the Wakely Consulting Group, LLC (Wakely Consulting Group (2020)). See Peterson-KFF (2020) for estimates ranging from approximately $10,000–$20,00 depending on comorbidities or Fair Health (2020) for alternative estimates ranging from $45,000-$75,000.

[31]See https://www.transportation.gov/sites/dot.gov/files/docs/2016%20Revised%20Value%20of%20a%20Statistical%20Life%20Guidance.pdf.

the CPS, we find that the unemployment rate increased dramatically during the pandemic, with larger increases for states that had issued stay-at-home orders. Our back of the envelope calculations related to the costs and benefits of state orders suggest that, as of early May: the lost income is \$18.6–\$21.4 billion; COVID-19 known cases are reduced by 186,600–311,000; costs to hospitals are down \$0.7–\$1.2 billion; unemployment benefit payments are \$5–\$5.8 billion higher; federal income tax revenue is \$2.5–\$3 billion lower; and deaths are reduced by 17,851–23,325. Despite the jobs lost, our results suggest that stay-at-home orders are cost effective. These results are important given the current tradeoff faced by state governors between employment and disease prevention (Eichenbaum et al. (2020)).

Our analysis also documented heterogeneous effects of COVID-19 and government response across occupations and workers. The findings suggest that COVID-19 and stay-at-home orders affect disproportionately younger, not married, non-white and less-educated workers. Moreover, occupations that work in proximity to others are more affected while occupations able to work remotely and essential workers are less affected by the pandemic. These results could lead workers to change (and students to choose different) occupation in the short- or medium-term, and move into less 'risky' ones. Similarly, COVID-19 may accelerate the rise in flexible work arrangements and telecommuting (Katz and Krueger (2019); Mas and Pallais (2017)).

Future work should consider the medium and long run economic impacts of COVID-19 and its impacts on human capital accumulation, early-life exposure and labor market discrimination (e.g., Schild et al. (2020)). In considering the long run economic consequences of the COVID-19 epidemics, one is drawn to other examples of epidemics such as the AIDS epidemics in sub-Saharan Africa, the Spanish Flu and the Black Death in Britain in the late fourteenth century (Barro et al. (2020)). Numerous studies point out that real wages rose after the Black Death (e.g., Goldberg (1992)) and that the AIDS epidemics may have increased the welfare of future African generations, possibly through an increase in female labor force participation and a decrease in fertility (Young (2005)). While the long-term economic consequences of COVID-19 remain unknown at this point, the human suffering brought on by the epidemic and its economic consequences are depressing in the short run.

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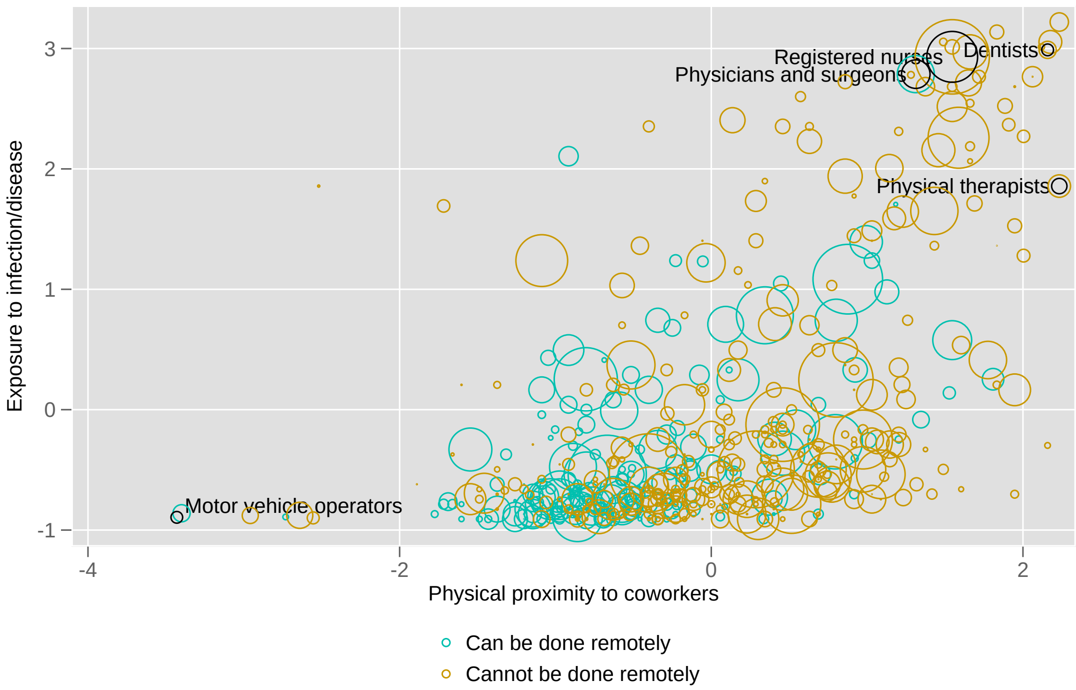
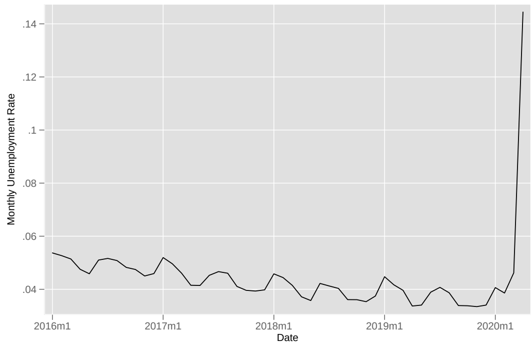
Figure 1: Physical Proximity, Exposure to the Disease and Remote Work by Occupation

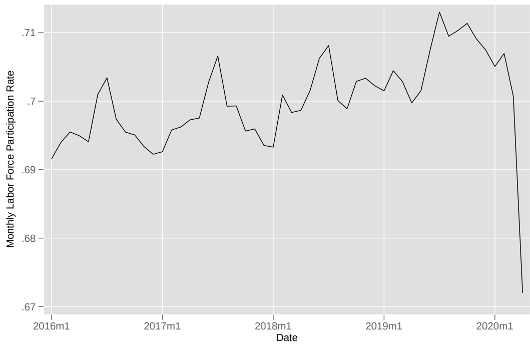


Notes: Each circle represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's physical proximity to coworkers, measured by O*NET's index. The further to the right, the closer in proximity employees in that occupation work with their coworkers. The y-axis plots each occupation's exposure to infection and disease, also measured by O*NET's index. The further up, the more frequently employees in that occupation are exposes to infection and disease. The color of the circles corresponds to the whether or not the occupation can be performed remotely via Dingel and Neiman (2020).

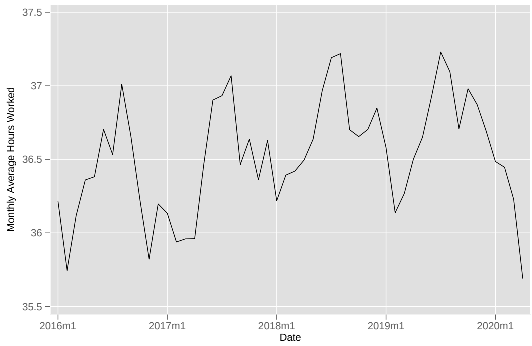
Figure 2: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages.



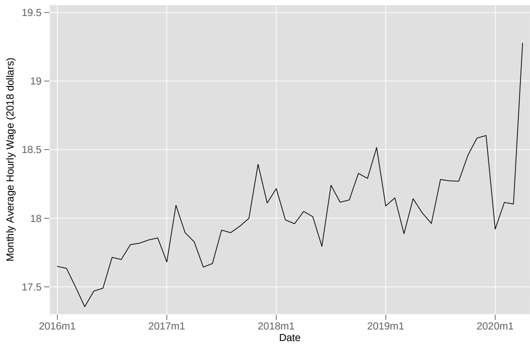
(a) Unemployment Rate.



(b) Labor Force Participation.



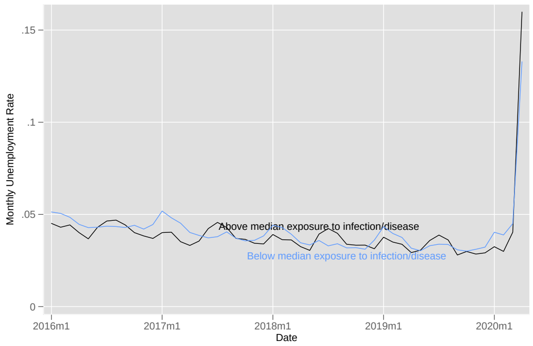
(c) Hours of Work.



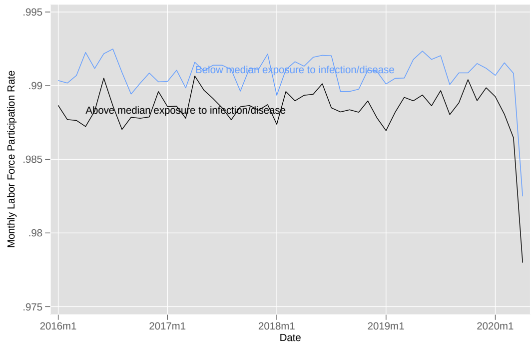
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

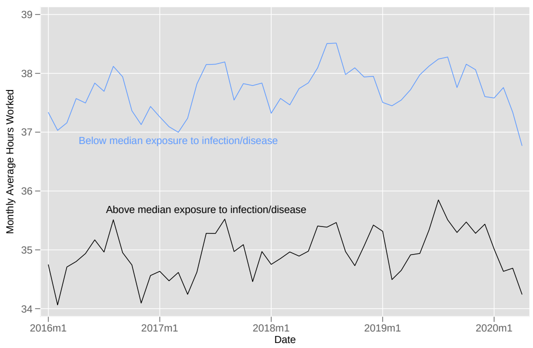
Figure 3: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Exposure to Disease.



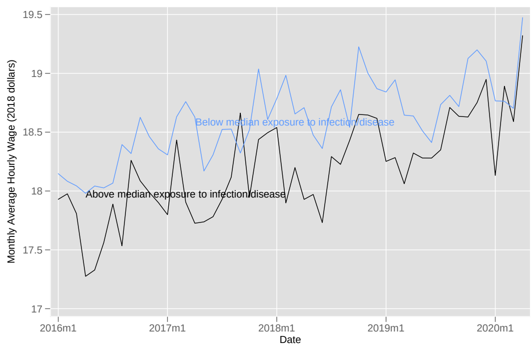
(a) Unemployment Rate.



(b) Labor Force Participation.



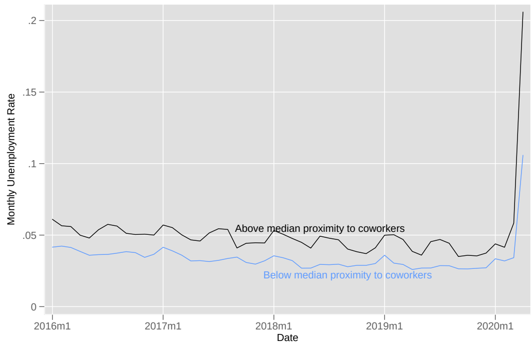
(c) Hours of Work.



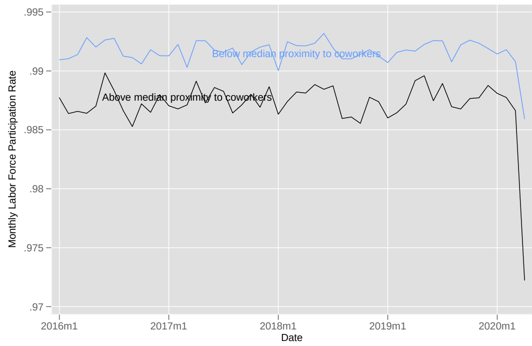
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for individuals in occupations above and below the median for our index of exposure to the disease. Panel B plots the labor force participation for individuals in occupations above and below the median for our index of exposure to the disease. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work for individuals in occupations above and below the median for our index of exposure to the disease. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages for individuals in occupations above and below the median for our index of exposure to the disease. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

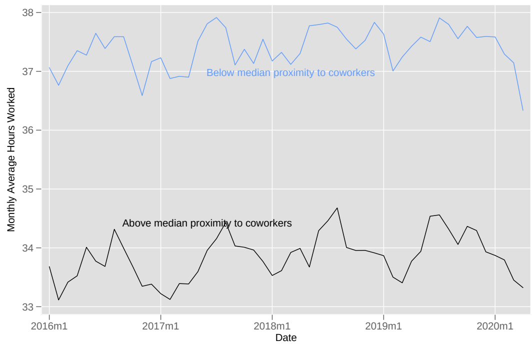
Figure 4: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Proximity to Coworkers.



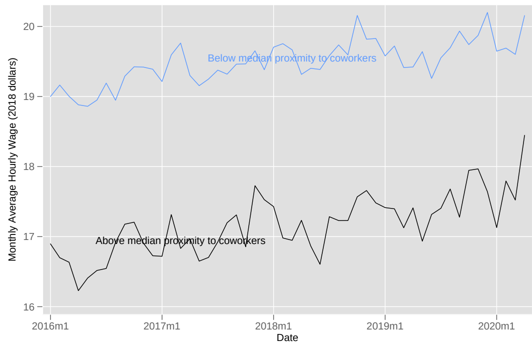
(a) Unemployment Rate.



(b) Labor Force Participation.



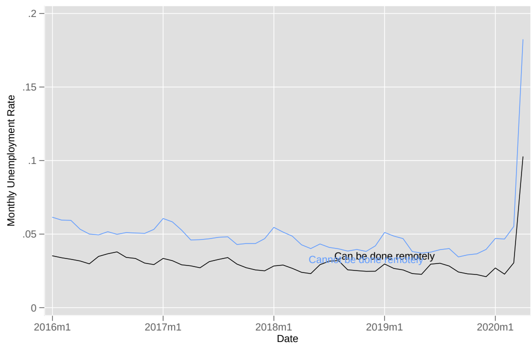
(c) Hours of Work.



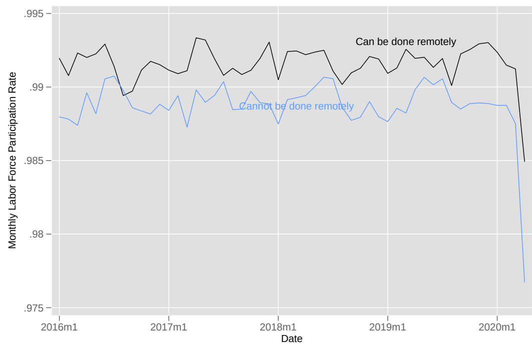
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for individuals in occupations above and below the median for our index of proximity to coworkers. Panel B plots the labor force participation for individuals in occupations above and below the median for our index of proximity to coworkers. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work for individuals in occupations above and below the median for our index of proximity to coworkers. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages for individuals in occupations above and below the median for our index of proximity to coworkers. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

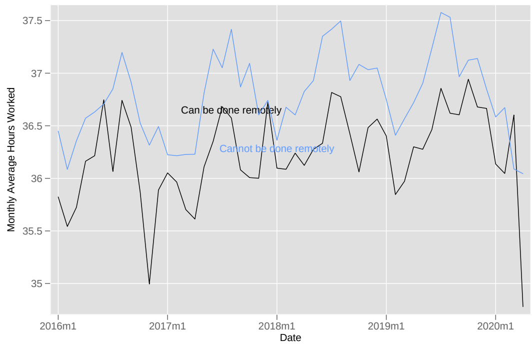
Figure 5: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Individuals in Occupations that Can/Cannot be done Remotely.



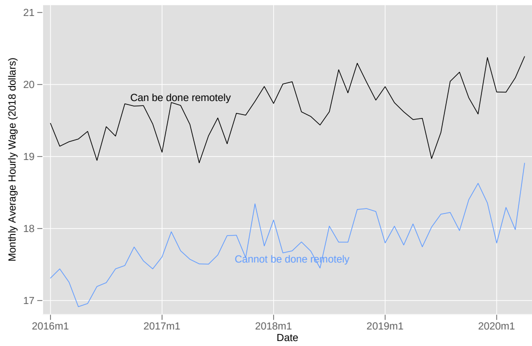
(a) Unemployment Rate.



(b) Labor Force Participation.



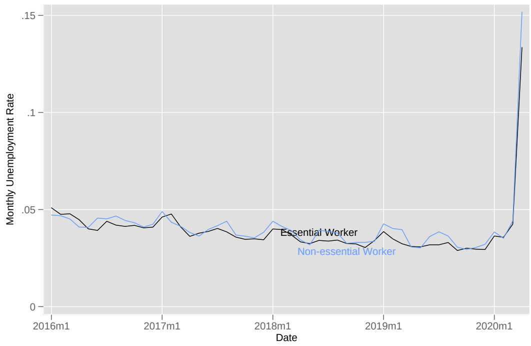
(c) Hours of Work.



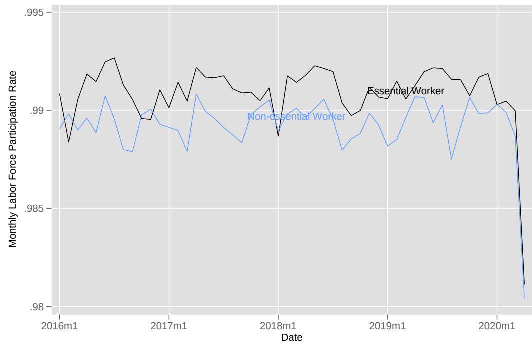
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for individuals in occupations designated by Dingel and Neiman (2020) as being able to be done remotely. Panel B plots the labor force participation for individuals in occupations that can be done remotely. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work for individuals in occupations that can be done remotely. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages for individuals in occupations that can be done remotely. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

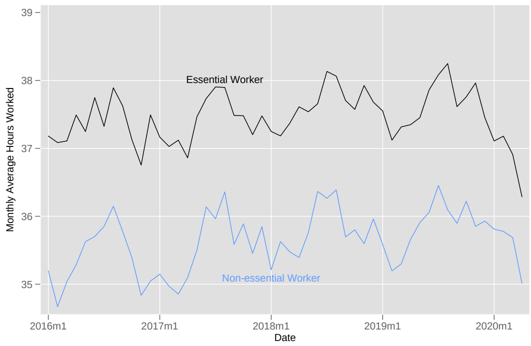
Figure 6: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Individuals in Non-Essential/Essential Occupations.



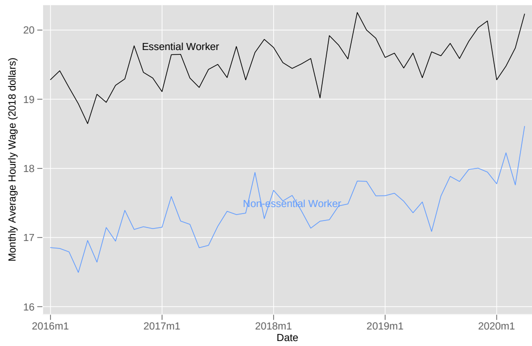
(a) Unemployment Rate.



(b) Labor Force Participation.



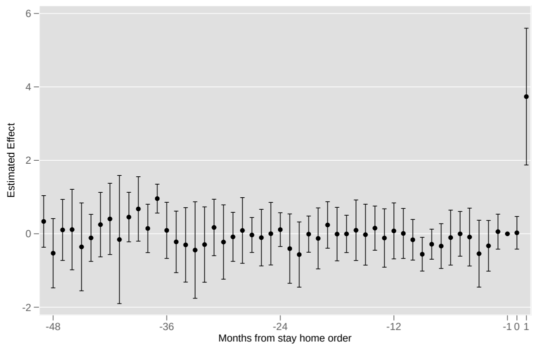
(c) Hours of Work.



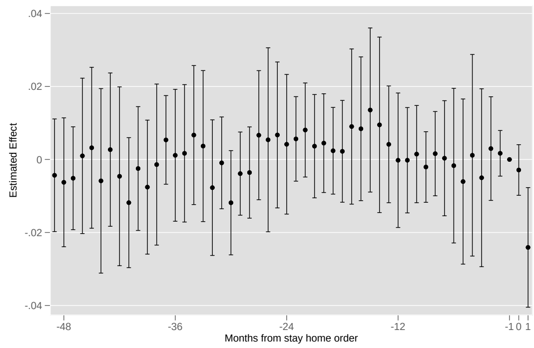
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for individuals in occupations designated as essential and non-essential by the Labor Market Information Institute. Panel B plots the labor force participation for individuals in essential or non-essential occupations. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work for individuals in occupations deemed essential and non-essential. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages for individuals in occupations deemed essential and non-essential. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

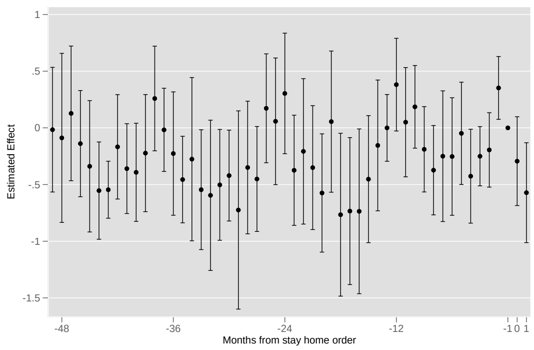
Figure 7: Stay Home Order Leads and Lags: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages



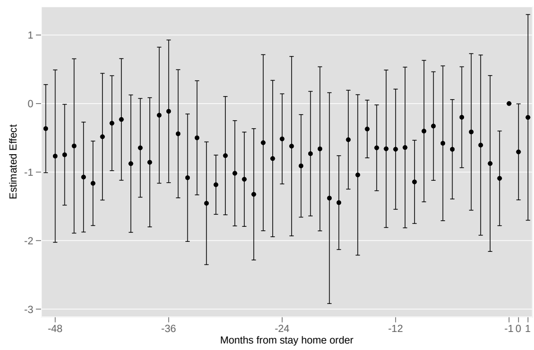
(a) Unemployment Rate.



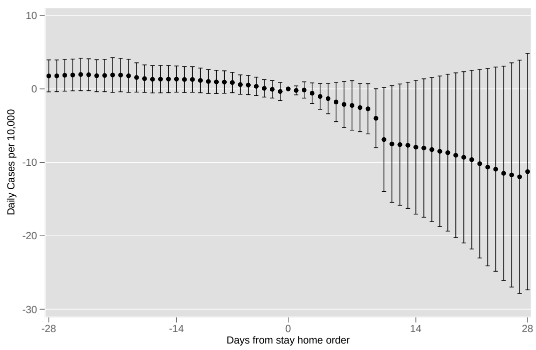
(b) Labor Force Participation.



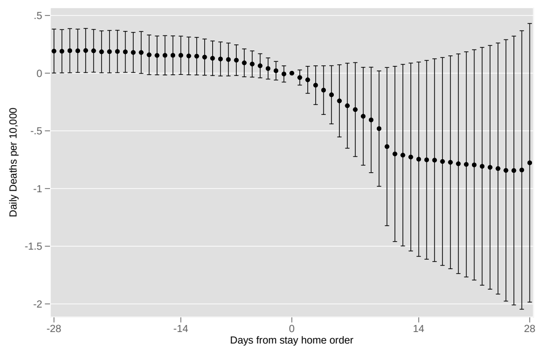
(c) Hours of Work.



(d) Hourly Wages.



(e) Cases per 10,000.



(f) Deaths per 10,000.

Notes: Data from the Current Population Survey. The time period for Panels A–D is March 2019 to April 2020. Panel A plots the estimated effect of stay-home orders on the average monthly unemployment rate for 11 months leading up to the stay home order and 1 month afterwards. Panel B plots the same but for labor force participation rate, Panel C shows the effect on hours worked while Panel D presents results for real hourly wage. Panels E and F show the estimated effects for average monthly COVID-19 cases per 10,000 inhabitants and COVID-19 deaths per 10,000 inhabitants, respectively.

Table 1: Descriptive Statistics

	Mean	S.D.	Max	Min	Count
Indexes					
Exposure to infection/disease index	-0.002	1.002	3.2	-0.9	3,090,005
Physical proximity to coworkers index	0.008	1.003	2.2	-3.5	3,090,005
Remote work index	-0.005	0.998	1.3	-0.8	2,896,179
Essential worker index	0.008	1.001	1.1	-0.9	2,975,856
Labor outcomes					
Unemployed	0.044	0.206	1.0	0.0	3,070,317
In labor force	0.705	0.456	1.0	0.0	4,378,703
Real hourly wages (2018 dollars)	17.76	8.855	61.4	4.8	390,852
Hours worked last week	38.98	12.663	198.0	1.0	2,836,277
COVID-19 outcomes					
Cumulative COVID-19 cases	3505.18	16300.89	180458	0.0	144
Cumulative COVID-19 cases per 10,000	3.990	10.981	92.8	0.0	144
Cumulative COVID-19 deaths	137.38	755.873	8627	0.0	144
Cumulative COVID-19 deaths per 10,000	0.140	0.471	4.4	0.0	144

Notes: Authors' calculations. Labor force participation: individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars. The descriptive statistics for the labor variables of interest are from January 2016 to April 2020. Cumulative COVID-19 cases, cases per 10,000 people, deaths, and deaths per 10,000 people are the cumulative totals corresponding to the last day of the week for which employment information is collected by the CPS. For COVID-19 outcomes we average over February, March, and April and each observation is a state-month.

Table 2: The Impacts of COVID-19: Exposure, Proximity and Remote Work

Panel A. Unemployed	Baseline	Exposure	Proximity	Remote Work	Essential
Post COVID	0.0613	0.0636	0.0636	0.0654	0.0640
	(0.0028)	(0.0027)	(0.0027)	(0.0029)	(0.0028)
Index		-0.0034	0.0007	-0.0037	-0.0013
		(0.0003)	(0.0004)	(0.0007)	(0.0002)
Index × Post		-0.0002	0.0177	-0.0190	-0.0041
		(0.0011)	(0.0011)	(0.0015)	(0.0013)
Observations	3070317	3058329	3058329	2866878	2945604
Panel B. Labor Force Participation	Baseline	Exposure	Proximity	Remote Work	Essential
Post COVID	-0.0222	-0.0052	-0.0052	-0.0055	-0.0053
	(0.0025)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Index		-0.0001	-0.0004	0.0002	0.0006
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index × Post		-0.0003	-0.0018	0.0017	-0.0002
		(0.0004)	(0.0005)	(0.0005)	(0.0004)
Observations	4378703	3090005	3090005	2896179	2975856
Panel C. Wages	Baseline	Exposure	Proximity	Remote Work	Essential
Post COVID	0.374	0.307	0.281	0.329	0.312
	(0.155)	(0.146)	(0.147)	(0.151)	(0.154)
Index		0.638	-0.0655	0.626	0.715
		(0.0356)	(0.0370)	(0.0702)	(0.0186)
Index × Post		0.0635	0.192	0.0725	0.0320
		(0.0952)	(0.0799)	(0.102)	(0.0862)
Observations	390852	364752	364752	343578	350383
Panel D. Hours	Baseline	Exposure	Proximity	Remote Work	Essential
Post COVID	-0.829	-0.801	-0.831	-0.848	-0.818
	(0.0764)	(0.0767)	(0.0760)	(0.0851)	(0.0858)
Index		-0.387	-0.691	0.511	0.331
		(0.0300)	(0.0536)	(0.0338)	(0.0163)
Index × Post		-0.0032	-0.0584	0.0778	-0.181
		(0.0641)	(0.0753)	(0.0817)	(0.0570)
Observations	2793158	2793158	2793158	2619263	2690316
Indiv. Chars	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is a dummy for whether the individual is unemployed. In the second, the dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. In the third panel, the dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. In the bottom panel, the dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. In column 1 of all panels, we provide baseline estimates without the indexes. Columns 2–5 provide estimates for our indexes. *Index* measures our exposure to disease index, proximity to coworkers index, remote work index, and essential worker index, respectively. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table 3: COVID-19-related Absences, Layoffs and Involuntary Part-time: Exposure, Proximity and Remote Work

Panel A. Unemployed	Baseline	Exposure	Proximity	Remote	Essential
Post COVID	0.495	0.498	0.484	0.490	0.496
	(0.0102)	(0.0097)	(0.0105)	(0.0105)	(0.0094)
Index		0.0034	0.0225	-0.0179	-0.0124
		(0.0025)	(0.0058)	(0.0031)	(0.0021)
Index × Post		0.0498	0.0379	-0.0145	0.0015
		(0.0074)	(0.0084)	(0.0082)	(0.0059)
Observations	129282	117294	117294	110265	112595
Panel B. Reduced Hours	Baseline	Exposure	Proximity	Remote	Essential
Post COVID	0.134	0.137	0.137	0.136	0.135
	(0.0053)	(0.0053)	(0.0054)	(0.0048)	(0.0047)
Index		-0.0071	-0.0034	-0.0134	0.0101
		(0.0008)	(0.0009)	(0.0009)	(0.0008)
Index × Post		-0.0097	-0.0081	0.0009	-0.0018
		(0.0031)	(0.003)	(0.0042)	(0.0033)
Observations	641356	641356	641356	595772	617725
Panel C. Absences	Baseline	Exposure	Proximity	Remote	Essential
Post COVID	0.406	0.415	0.405	0.414	0.410
	(0.0207)	(0.0205)	(0.0202)	(0.0200)	(0.0202)
Index		-0.008	0.0021	0.0140	-0.0179
		(0.0014)	(0.0016)	(0.0017)	(0.0011)
Index × Post		-0.0314	0.0173	-0.0178	-0.0081
		(0.0055)	(0.0078)	(0.0102)	(0.0083)
Observations	104758	104758	104758	98126	101538
Indiv. Chars	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is a dummy that equals one if an individual's explanation for unemployment falls into the BLS advised category for COVID-19 related layoffs. In the second panel, the dependent variable is a dummy that equals one if the individual's explanation for working part-time hours when usually full-time calls into the BLS advised category for COVID-19 related slack. In the bottom panel, the dependent variable is a dummy that equals one if the individual's explanation for why they were absent at their job in the reference week falls into the "other" category the BLS identifies as being a location for misclassified workers. In column 1 of all panels, we provide baseline estimates without the indexes. Columns 2–5 provide estimates for our indexes. $Index$ measures our exposure to disease index, proximity to coworkers index, remote work index, and essential worker index, respectively. $Post\ COVID$ is a dummy that is equal to one for the month of April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016– April 2020.

Table 4: COVID-19 Deaths and Labor Market Outcomes: State-Level

	Unemployed				In labor force			
	Cases		Deaths		Cases		Deaths	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative COVID-19 cases/deaths per 10,000 people	0.0021	0.0084	0.0407	0.177	-0.0007	-0.0027	-0.0140	-0.0506
	0.0006)	(0.0011)	(0.0129)	(0.0321)	(0.0002)	(0.0004)	(0.0026)	(0.0145)
$Case/deathrate^2$		-0.0001		-0.0349		0.0000		0.0093
		(0.0000)		(0.0072)		(0.0000)		(0.0033)
Observations	3070317	3070317	3070317	3070317	4378703	4378703	4378703	4378703
	Wage				Hours			
	Cases		Deaths		Cases		Deaths	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative COVID-19 cases/deaths per 10,000 people	0.0118	0.0665	0.241	1.610	-0.0140	-0.0901	-0.242	-1.631
	(0.0079)	(0.0179)	(0.183)	(0.399)	(0.0074)	(0.0157)	(0.132)	(0.405)
$Case/deathrate^2$		-0.0007		-0.361		0.0001		0.359
		(0.0002)		(0.0871)		(0.0002)		(0.0885)
Observations	390852	390852	390852	390852	2793158	2793158	2793158	2793158
Indiv. Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. Columns 1–2 and 5–6 correspond to cumulative cases per 10,000 while 3–4 and 7–8 correspond to deaths per 10,000. In the top panel, columns 1–4, the dependent variable is a dummy for whether the individual is unemployed. In the top panel, columns 5–8, the dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. In the bottom panel, columns 1–4, the dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. In the bottom panel, column 5–8, the dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. *Cumulative cases/deaths per*10,000 is a variable equal to the number of cumulative number of confirmed COVID-19 cases or deaths per 10,000 inhabitants in the state. All columns include state, month, year, region × year, and interview type fixed effects and the following demographic controls: gender, age, education marital status and race. The time period is January 2016–April 2020.

Table 5: Effect of Stay-at-Home Policies: Differences-in-Differences

Panel A. Labor Market Outcomes

	Unemp. Rate	Hours	Wages	LFP
State order	3.773	-0.335	0.513	-0.0247
	(0.765)	(0.270)	(0.536)	(0.0043)
Observations	2652	2652	2652	2652
Month × Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Panel B. COVID-19 Outcomes

	Case Rate	Death Rate	Case Rate No Incubation	Death Rate No Incubation
State order	-0.899	-0.255	-6.00	-0.574
	(0.497)	(0.124)	(3.47)	(0.307)
Observations	3360	3360	2880	2880
Month × Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Linear State Time Trend	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey and The COVID Tracking Project. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable in column 1 is the average monthly unemployment rate, in column 2 it is the average monthly hours worked, column 3 is average monthly real hourly wage, column 4 is average monthly labor force participation. In Panel B, the dependent variable in column 1 is COVID-19 cases per 10,000 people; in column 2 is COVID-19 deaths per 10,000 people. Columns 3 and 4 of Panel B have the same dependent variables as columns 1 and 2, respectively, but exclude the first 11 days after the policy is implemented to account for the virus incubation period.

Table 6: Effect of Stay-at-Home Policies: Differences-in-Differences with Social Distancing Controls

	Unemp. Rate		Hours		Wages		LFP	
State order	3.828	2.849	-0.458	-0.219	0.113	0.263	-0.022	-0.015
	(1.179)	(1.258)	(0.283)	(0.338)	(0.850)	(0.873)	(0.009)	(0.009)
Non-essential visits		-6.269		5.443		7.461		0.0173
		(14.26)		(2.942)		(5.444)		(0.0622)
Human encounters		0.194		-0.0037		0.0400		0.0015
		(0.270)		(0.0555)		(0.135)		(0.0019)
Travel distance		-13.44		-1.945		-6.554		0.0666
		(15.43)		(2.390)		(4.290)		(0.0551)
Observations	144	144	144	144	144	144	144	144
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey and The COVID Tracking Project. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable in column 1 is the average monthly unemployment rate, in column 2 it is the average monthly hours worked, column 3 is average monthly real hourly wage, column 4 is average monthly labor force participation. In Panel B, the dependent variable in column 1 is COVID-19 cases per 10,000 people; in column 2 is COVID-19 deaths per 10,000 people. Columns 3 and 4 of Panel B have the same dependent variables as columns 1 and 2, respectively, but exclude the first 11 days after the policy is implemented to account for the virus incubation period.

Appendix: NOT FOR PUBLICATION

5.1 Deviations from Pre-Analysis Plan and Previous Versions

In this study, we test the hypotheses, and rely on the specifications, detailed in our pre-analysis plans (PAP). The use of PAPs was designed to minimize issues of p-hacking and helping us think through, and collect, the data required for our analyses. Our first pre-analysis plan was archived on March 30, 2020, at https://osf.io/c28t5/. CPS data for the month of March 2020 were released mid-April 2020. Our discussion paper started circulating with our preliminary results as of April 20, 2020 (Beland, Brodeur and Wright (2020b)).

Following the feedback received, we made some modifications to the analysis. We provide a detailed description of the changes made in what follows. Furthermore, we added supplementary analyses in a second pre-analysis plan prior to the release of the April 2020 CPS data. In these analyses we investigate the impacts of government interventions on COVID-19 transmission and economic outcomes. Note that the March 2020 data did not allow us to evaluate these policies, i.e., stay-home orders, since they were implemented after the CPS reference week for March 2020.

Our pre-analysis plan indicated that we would measure remote work by creating an index using the American Community Survey's question about travel to work. Our current version of the paper presents this analysis in Appendix 5 and uses instead the classification developed by Dingel and Neiman (2020). We make this alteration to address concerns that our measure of remote work prior to COVID-19 may be capturing preferences, or wealth effects rather than the potential for occupations to be done remotely. In contrast, the Dingel and Neiman (2020) measure classifies occupations based on tasks and so better reflects the ease with which occupations can be done from home. Additionally, at the time of our pre-analysis plan, this classification was not available.

A previous version of this paper unintentionally applied the restrictions from hourly wages (trimming the 1st and 99th percentiles of the wage distribution) to hours worked. This resulted in estimates of the effects of COVID-19 on hours worked only for individuals with hourly wage data, i.e., those in the CPS outgoing rotation group, rather than the intended sample of all individuals with hours worked data (less those in the 1st and 99th percentile of the hours worked distribution and those outside ages 16–70). This modification has no effect on our point estimates or conclusions.

Our second pre-analysis plan indicated that we would control for the date of first confirmed COVID-19 known case for the differences-in-differences analysis. We do not as this variable is collinear. It also indicated that we were to include month and week of year fixed effects. This was a transcription error, it should have read *month by year* fixed effects.

Our pre-analysis plans did not include the analysis presented in Table 6. The results presented in this table should thus be viewed as exploratory analysis.

5.2 O*NET Index calculations

O*NET's indexes for "Exposure to infection and disease" and "Physical proximity to others" are created based on survey responses. These survey responses are collected on a 1–5 scale (the values for each questions are shown in Figures A11 and A12) and then converted into an index with the following formula:

$S = ((O - 1)/(H - 1)) * 100$

where S is the new index value, O is the original score on the 1–5 scale, and H is the highest possible score. As an example, a collected score of 4 becomes 75 $(= (4 - 1)/(5 - 1)) * 100)$.

We note that while we do not aggregate any of our indexes, some respondents give insufficient detail to have their occupation placed in the most detailed occupational code and are placed in a broader category. These groups are given weighted values of our indexes as described in the text.

5.3 COVID-19 and Work Arrangement

Via email correspondence, the BLS indicated that "BLS (working with the Census Bureau) supplied special instructions to CPS interviewers regarding questions related to the measurement of persons at work part time for economic reasons and persons on temporary layoff. Those instructions are described here:

https://www.bls.gov/cps/employment-situation-covid19-faq-march-2020.pdf (Question 7).

We did not supply special Coronavirus-related guidance regarding other labor force questions in the survey.

The basic CPS does not regularly include questions regarding telework/work at home. However, there is a proposal to add questions to the survey beginning with the collection of data for May; if approved, these questions should provide some insight into telework and other labor market developments associated with the pandemic:

https://www.reginfo.gov/public/do/PRAViewDocument?ref_nbr=202004-1220-008 (see supporting statement A).

Appendix Figure A47 presents the share of workers whose usual work activities or duties have changed since last month. Typically, just under 1% of respondents are changing their work activities. However, since December 2019 this has doubled, from 0.7% to nearly 1.4%, with a 0.2 percentage point increase in March 2020.

Appendix Table A24 presents the results for a dependent variable that equals one if an individual has changed work activities or duties since the previous month. The top panel shows an increase in the probability of workers reporting changes in work activities after COVID-19 (an increase of about 0.2 percentage points, statistically significant at the 5% level). For $Cumulative\ Cases\ per 10,000$, we're seeing positive point estimates (of about 0.4 percentage points for an increase of 1 case per 10,000) but not statistically significant at conventional levels.

Appendix Table A25 provides estimates for the interaction of our indexes with $Post\ COVID$. None of the interactions are statistically significant below the 50% level and they are all at least an order of magnitude smaller than the $Post\ COVID$ effect. In terms of signs, all interactions are positive but the exposure control is negative while the essential worker control is positive. This indicates that workers who are more exposed are less likely to see work arrangement changes while those who are essential workers are more likely to see see their arrangements change. However, we are not able to detect a difference workers along our indexes before and after COVID-19.

5.4 Labor Market Outcomes by Socioeconomic Groups

Appendix Figures A15, A16, A17, A18 and A19 illustrate our four labor market outcomes by gender, age groups, marital status, race and education groups, respectively. For the analysis by gender presented in Appendix Figure A15, we find that both male and female are negatively affected by the pandemic. Our graphical evidence suggests that the decreased in employment rate is larger for women.

We next document the impact of COVID-19 by age groups. Appendix Figure A16 presents separate results by age groups. It shows that the pandemic affects the labor outcomes of all age groups but the decline appears more pronounced for younger workers for unemployment and labor force participation. In contrast, the impact of COVID-19 is larger on middle-aged adults for hours of work.

We next document the impact of COVID-19 by marital status. Appendix Figure A17 shows that both married and non-married's employment are negatively affected, with larger effects for not married individuals.

Appendix Figure A18 splits the sample by race. It presents results for Whites, Blacks, Hispanics and Asians separately. This figure illustrates that all groups are negatively affected by COVID-19 but the decline in employment, labor force participation and hours of work seem larger for Asians, Blacks and Hispanics, compared to white. The largest increase in unemployment is for Hispanics. Hispanics are less likely to have health insurance and more likely to work in the leisure, hospitality and other service industries, which could explain the more pronounced impact of

COVID-19 on this group.

Next, in Appendix Figure A19 we present results by educational attainment. We split individuals in three groups: (1) less than high school, (2) high school degree, and (3) associate-bachelor or graduate degree. Appendix Figure A19 shows that the negative impact of COVID-19 on employment is less pronounced on associate-bachelor or graduate degree workers.

Appendix Figure A20 presents the results separately for immigrants and native born. It suggests that the labor market impact of COVID-19 is significantly more pronounced for immigrants than native born workers. Immigrants experienced an increase in the unemployment rate of more than 12 percentage points and a decrease in both hours of work and labor force participation. In contrast, native born workers experienced an increase of about 10 percentage points in the unemployment rate and a small decrease in hours of work. This is potentially troublesome due to the well known labor market gap between native born and immigrant workers.

Appendix Tables A4, A5, A6 and A7 confirm these patterns. We interact our variable of interest, $Post\ COVID$, with a dummy for male respondents in column 1, dummies for the age categories 16–34 and 35–54 in column 2, a dummy for being married in column 3, and our four race dummies in column 4, respectively. White being the omitted category. We find that women are more likely to be unemployed as a result of the pandemic but that men are more likely to exit the labor force and the large decline in wages suggests those exiting have lower wages. We also find that COVID-19 has larger effects on younger workers' (aged 16 to 34) unemployment and labor force participation. Moreover, these tables find smaller negative effects for married individuals for unemployment and labor force participation. We also find that that Hispanics, Asian and Other race are significantly more likely to be unemployed due to COVID-19 than whites. We also find that the labor force participation of Blacks is significantly more negatively affected than whites. Overall, these results suggest an increase in labor market inequalities.

5.5 Labor Market Outcomes by Major Occupation Groups

Appendix Figures A21–A42 present plots of the monthly unemployment rate, labor force participation rate, hourly wages, and hours worked for each of the 23 major occupational groups found in the SOC.

In general, most occupations experienced a sharp increase in the unemployment rate in April 2020. The smallest increases are for computer and mathematical, life, physical, and social science, community and social service, and legal. The largest increases in unemployment are for construction, production, food preparation and serving related occupations, arts, design, entertainment, sports, and media, maintenance, sales, personal care and service and transportation and material moving.

Of particular interest are the labor market outcomes for health workers, found in Appendix Figures A30 and A31. Unemployment actually fell for healthcare and support occupations in March and but increased drastically in April. For healthcare practitioners and technical occupations, the increase in unemployment was much more modest.

5.6 Unacast COVID-19 Dashboard Data

As one of our pre-treatment characteristics and in the analysis on the impacts of stay-at-home orders, we employ the three metrics Unacast developed for their Social Distancing Scoreboard:

https://www.unacast.com/covid19/social-distancing-scoreboard.

They create a human encounter metric which identifies encounters as two mobile devices being within 50 meters of each other over a 60 minute window, normalized by land area (per square kilometer) and then divided by the baseline level of encounters in the four weeks leading up to COVID-19. They create another metric measuring visits to non-essential venues using guidance documents provided by governments and other policy makers, comparing day specific traffic to those locations from the baseline period prior to the COVID-19 pandemic (March 8th and earlier). Lastly, we use their measure of average distance travelled which computes the rate of change in distance traveled in a similar way to the reduction in non-essential venue travel.

5.7 Synthetic Control Methods

5.7.1 Synthetic Control Method: Identification Strategy As a robustness check to our differences-in-differences strategy, we rely on synthetic control methods (Abadie et al. (2010)) to generate a pool of control states. These synthetic controls states are meant to reproduce the health and economic outcomes that would have been observed for states implementing the stay-at-home orders in the absence of those policies.

For the synthetic control exercise, we restrict the donor pool of states to those that had not implemented a policy up to seven days after the treated state. For example, California implemented its order on March 19, 2020 and so we restrict donor states to those states who had not implemented a stay-at-home orders as of March 26, 2020. This restriction is necessary to detect an effect, as using states that implement a stay-at-home order almost at the same time would strongly drive our estimates towards zero. Of note, our estimates of COVID-19 cases and deaths are still biased towards zero as the states in the donor pool do eventually become treated (i.e., after seven days).

We use monthly state-level labor market data provided by the CPS to estimate the effects of the stay-at-home orders on the monthly unemployment rate, labor force participation rate, average hourly wages, and average hours worked. The vector of pre-intervention characteristics includes the previous 12 months of the dependent variable as well as the average value of Unacast's distance travelled, non-essential visits, and human encounter metrics.

For the effect of stay-at-home orders on COVID-19 known cases, we use a U.S. daily state-level panel of COVID-19 known cases per 10,000 inhabitants. Our sample begins on February 24, 2020 as this is the first day that we can obtain Unacast's social distancing data. When estimating the effect of the stay-at-home orders on these variables, we create our synthetic controls by including our vector of pre-intervention characteristics COVID-19 cases per 10,000 inhabitants as of the day prior to the policy's introduction (for California, this would be March 18, 2020). We estimate the effects up to May 3, 2020.

Constructing synthetic controls based on pre-treatment values of our outcomes of interest is a key piece of generating the appropriate control groups. Following our pre-analysis plan, we do not estimate the effects for COVID-19 related deaths as the number of deaths prior to the implementation of state order does not provide enough variation to generate appropriate matches.

5.7.2 Synthetic Control Method: Results As of April 7, 2020 there were 43 states with such orders but the optimization procedure is unable to construct synthetic versions of 3 states (Maryland, North Carolina, and Virginia), leaving us with estimates for 40 states. Additionally, we are concerned with the reliability of estimates for states with a severe reliance on a single donor state and as such do not present results for states where any single state receives a weight of greater than 0.66 for COVID-19 cases per 10,000, leaving us with estimates for 20 states. We apply this restriction to any outcome so that we are better able to compare the estimates for all outcomes with confidence. Treatment effects are defined as the treated state's value of the outcome less the synthetic control's value of the outcome.

Figure A48 plots population weighted averages of our state-level estimates over time. We confirm the sharp rise in unemployment associated with COVID-19 and an approximately 4 percentage point larger increase for states implementing a stay-at-home order than their synthetic controls. These unemployment estimates correspond very closely to those from our difference-in-difference approach. Labor force participation fell dramatically for both the synthetic and treated states but the decline appears to be larger for treated states by 0.8 percentage points.[32] Hourly

[32]It is worth nothing that the effect seems to precede the implementation of the stay-at-home

wages seem to increase during the COVID-19 period for both treated and synthetic states but it is difficult to declare wages to be higher or lower in treated states as the results are rather noisy and the pre-treatment match seems less stable than for our other outcomes. This ambiguity in estimates for the effects of stay-at-home orders on hours and wages is in line with our differences-in-differences estimates.

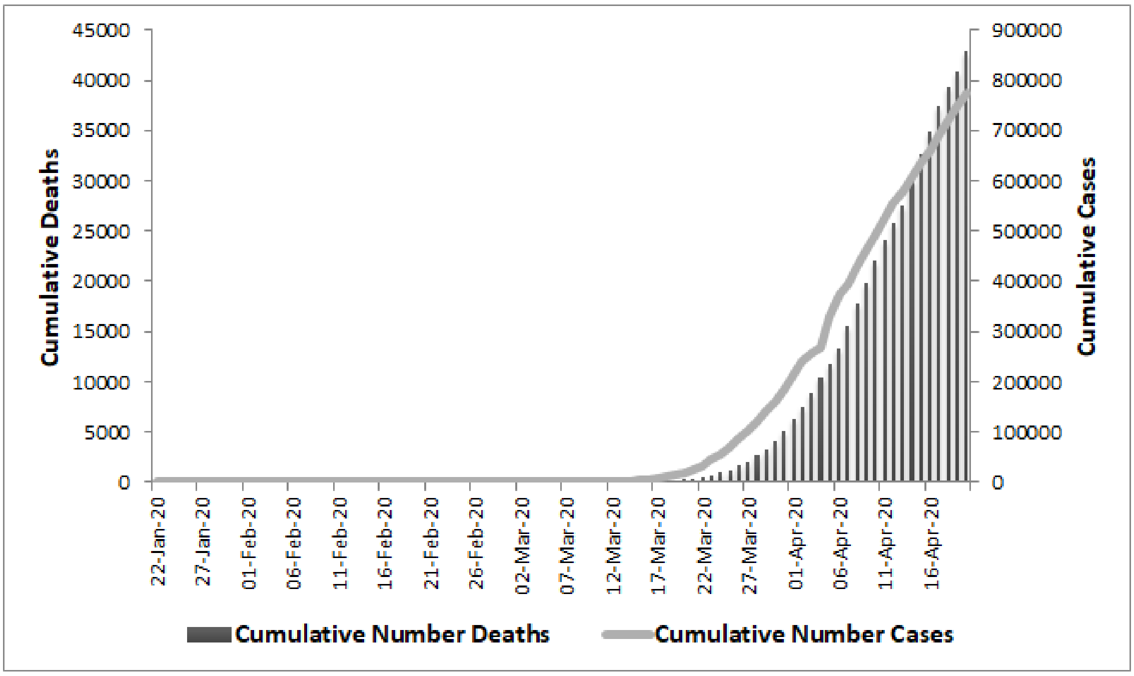
We now turn to estimating the impact of stay-at-home orders on COVID-19 known cases. As mentioned before, we are matching on pre-order social distancing measures as well as pre-order case, death, and testing rates. Of note, synthetic control methods may introduce an important issue. Recall that we construct the donor pool by restricting the states eligible for receiving weights to those that did not announce their own stay-at-home order up to 7 days afterwards. This means that we may severely underestimate the impacts of stay-at-home orders on COVID-19 cases and deaths as states whose responsiveness to the policy is most similar are ineligible for selection into the synthetic. Such a restriction is required in order to help avoid contamination of the states comprising the donor pool and provide enough lead time to evaluate the early returns on the policy.

Appendix Figure A48 plots the population weighted average COVID-19 cases per 10,000 inhabitants by day for both states with and without stay-home orders. There is evidence that states with orders have lower case rates than their synthetic counterparts, with the gap appearing to widen over time.[33]

orders, which suggests that our matching exercise is perhaps less reliable for labor force participation.

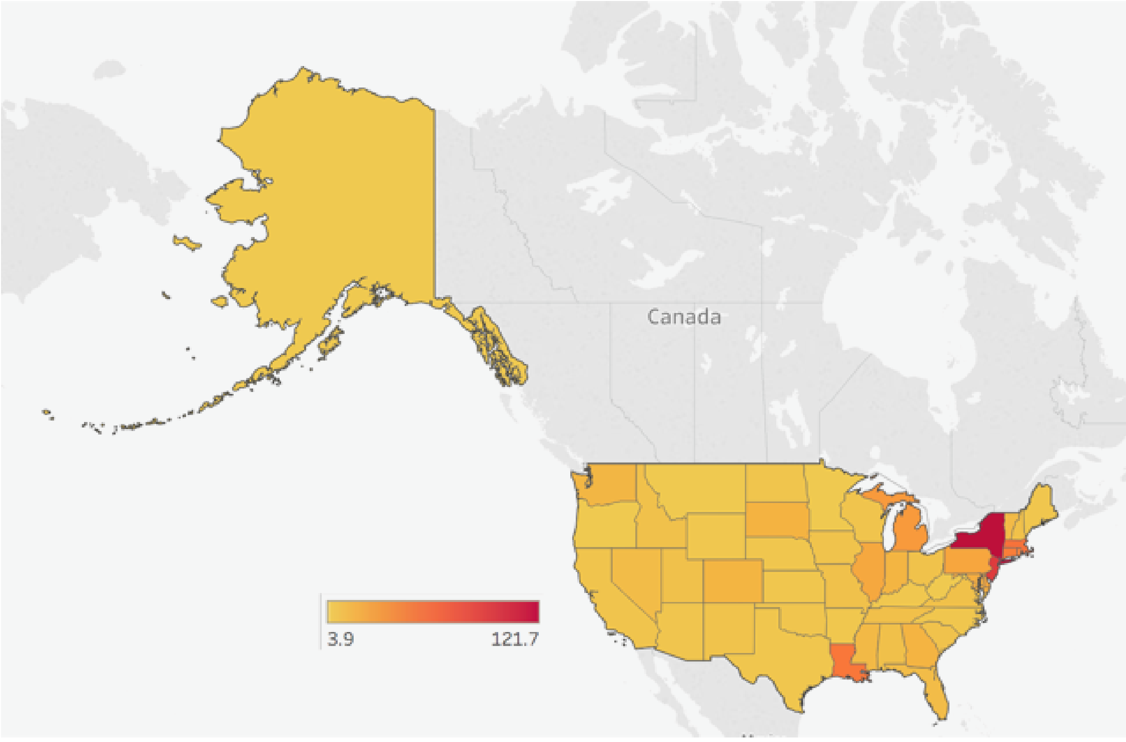
[33] Appendix Table A26 provides summary statistics of our estimated effects for each outcome.

Figure A1: COVID-19 Confirmed Cases in the United States



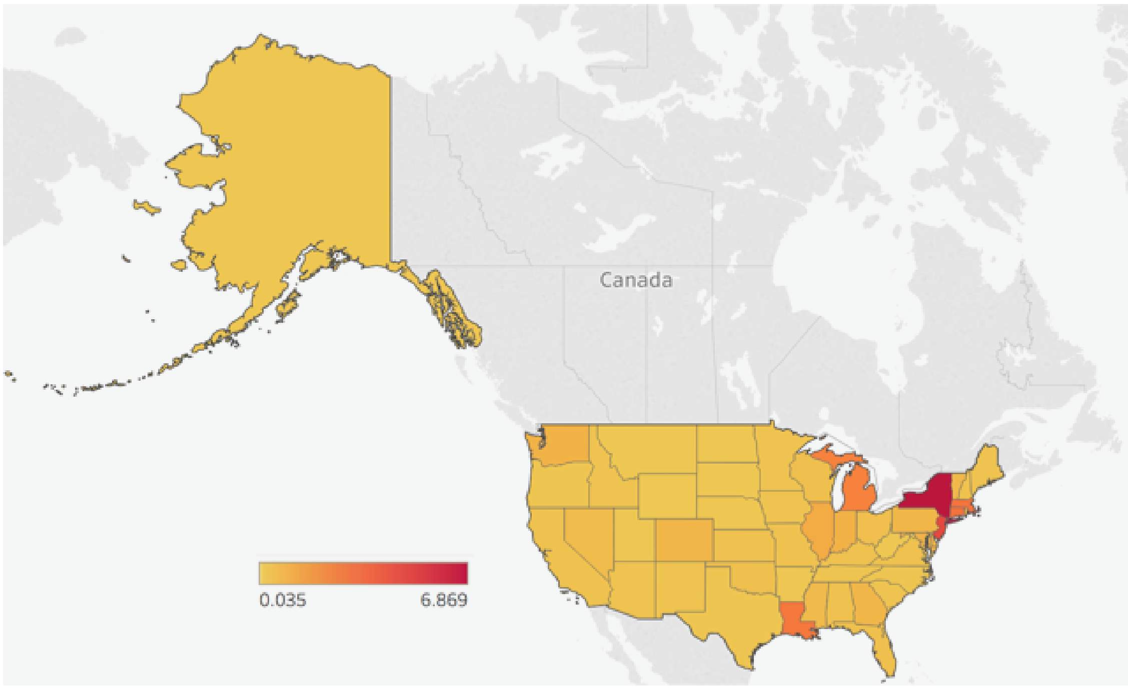
Notes: The primary vertical axis illustrates the cumulative number of COVID-19 deaths in the United States. The second vertical axis shows the cumulative number of (confirmed) COVID-19 cases in the United States. The data does not include cases among persons repatriated to the U.S. from Wuhan, China and Japan.

Figure A2: COVID-19 Confirmed Cases per 10,000 by State



Notes: The map illustrates the cumulative number of (confirmed) COVID-19 cases per 10,000 inhabitants for each state as of April 18, 2020.

Figure A3: COVID-19 Deaths per 10,000 by State



Notes: The map illustrates the number of COVID-19 deaths per 10,000 inhabitants for each state as of April 18, 2020.

Figure A4: Number of States with at Least One Confirmed Case

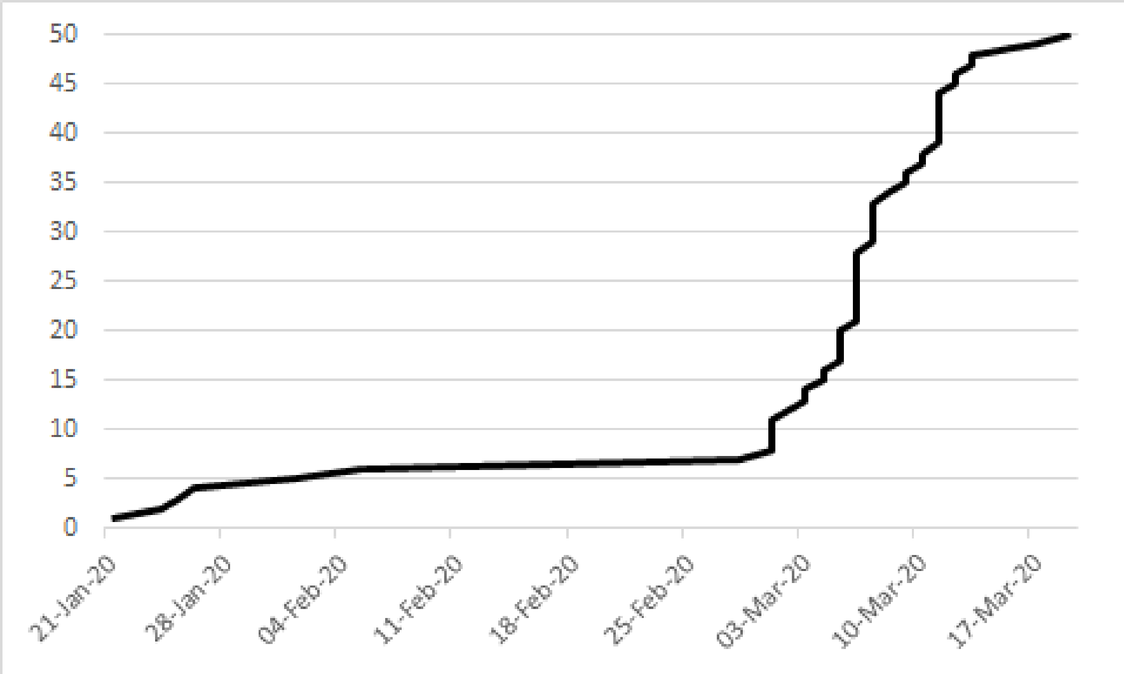


Figure A5: Number of States with at Least One Death

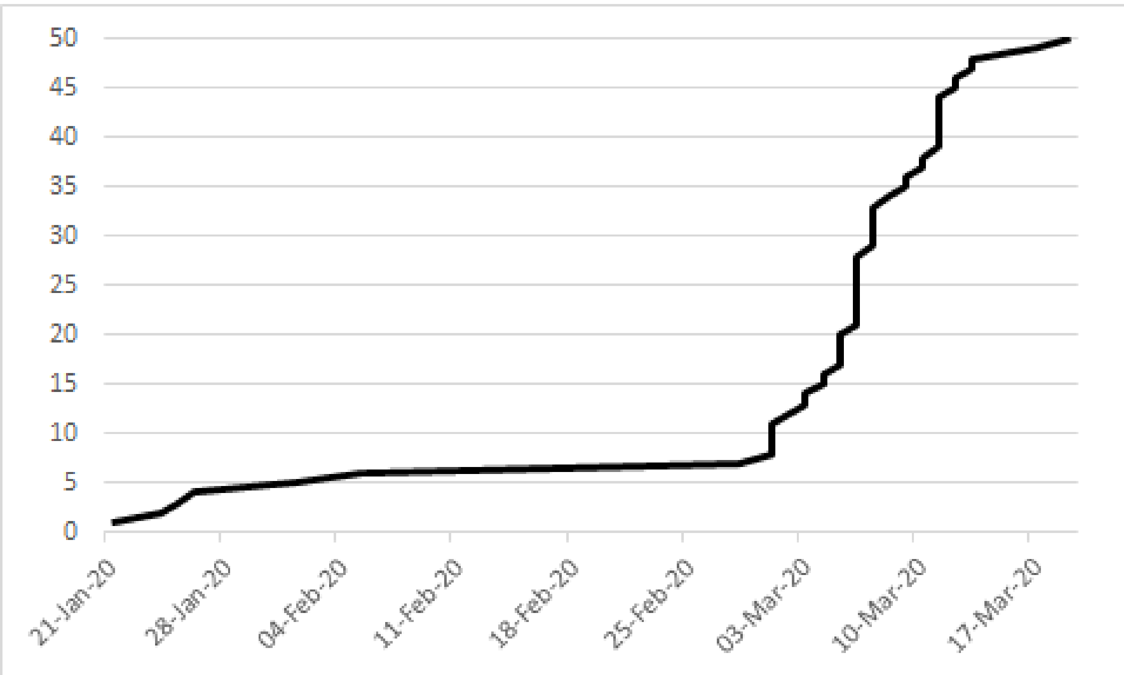


Figure A6: Timeline in the United States

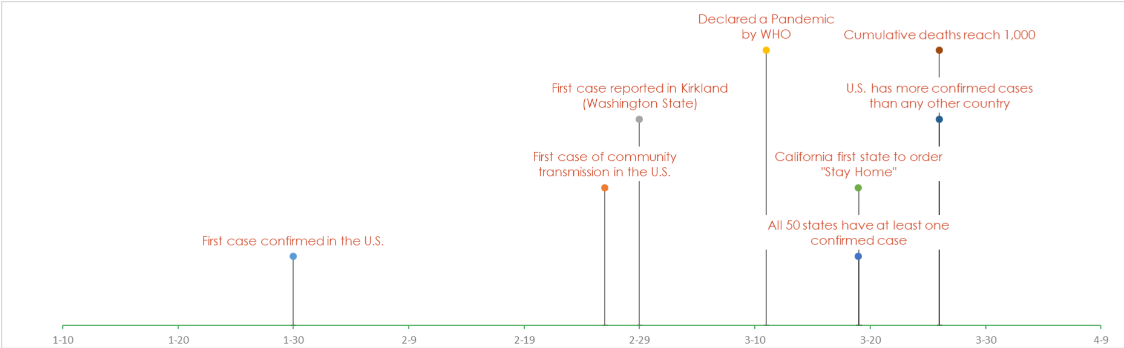
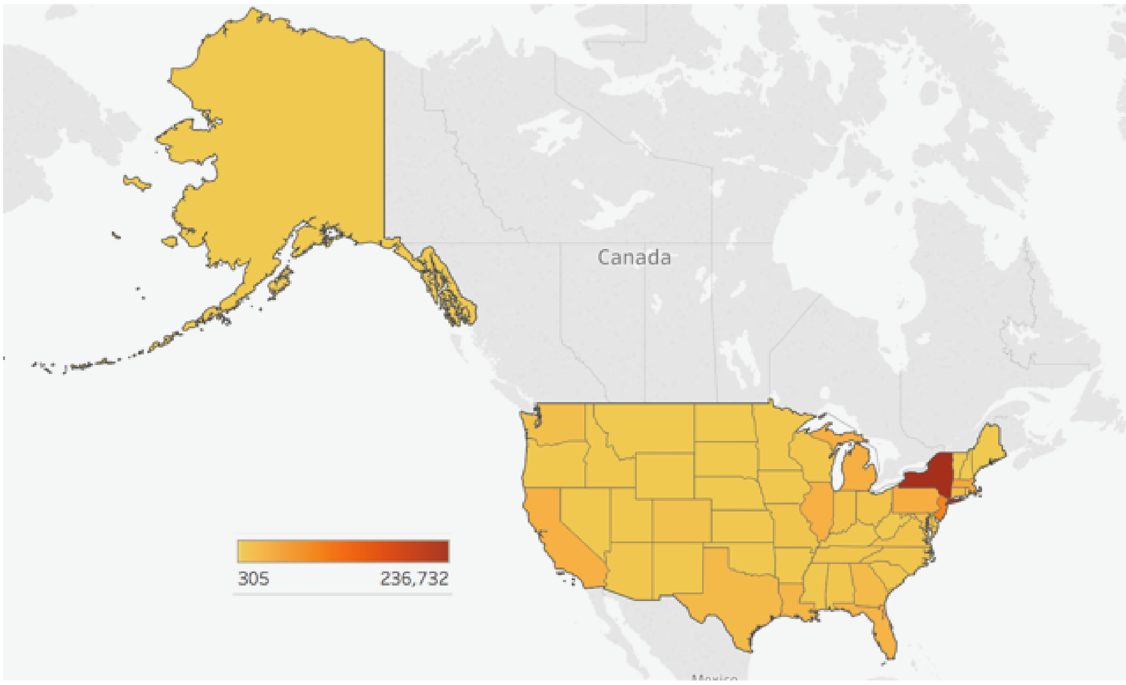
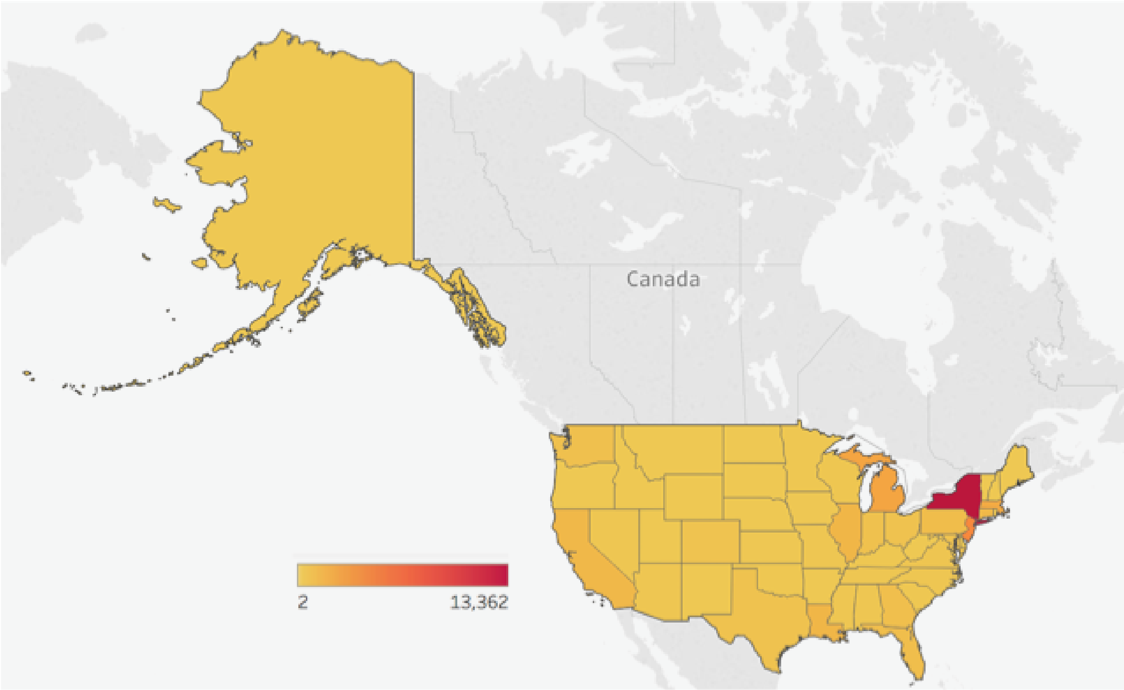


Figure A7: COVID-19 Confirmed Cases by State



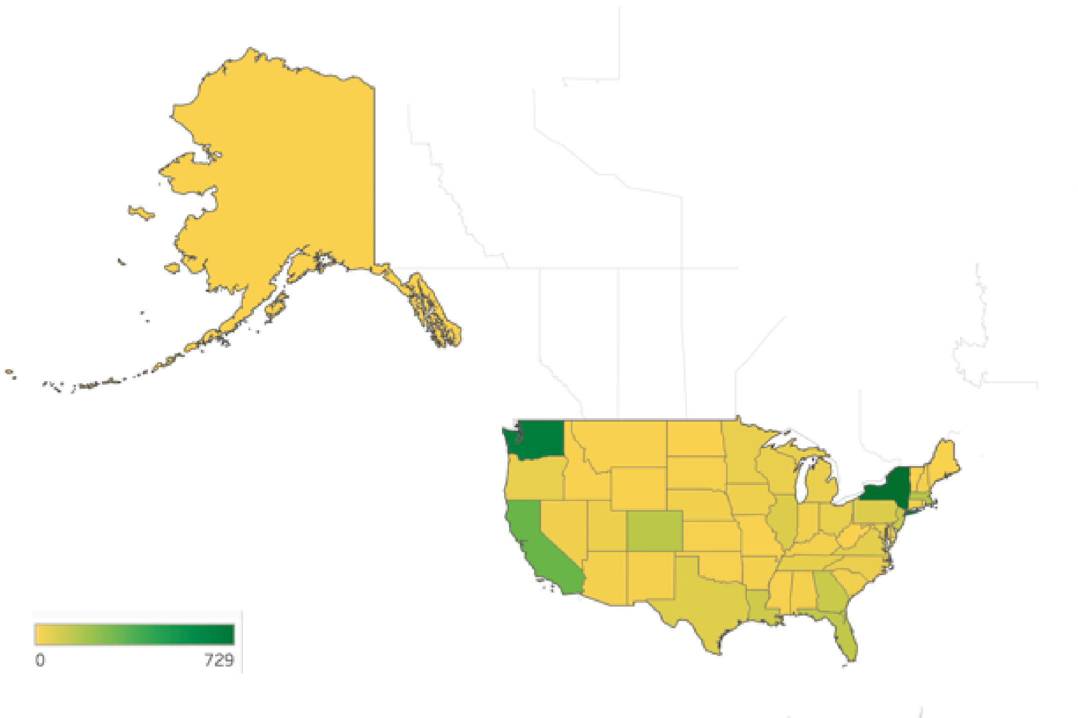
Notes: The map illustrates the cumulative number of (confirmed) COVID-19 cases for each state as of April 18, 2020.

Figure A8: COVID-19 Deaths by State



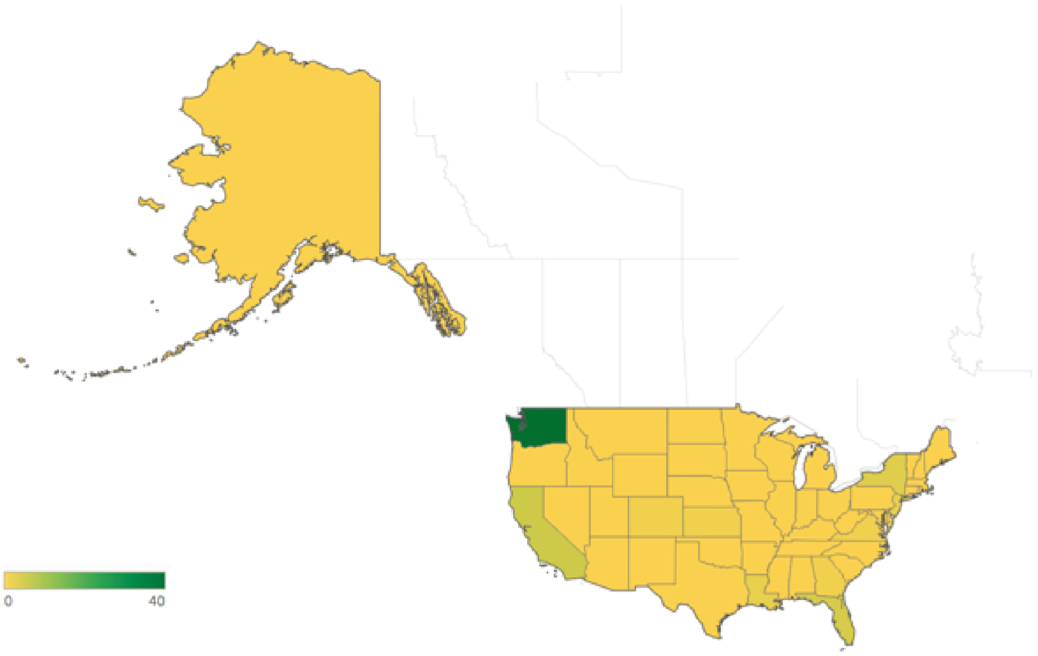
Notes: The map illustrates the number of COVID-19 deaths for each state as of April 18, 2020.

Figure A9: COVID-19 Confirmed Cases by State



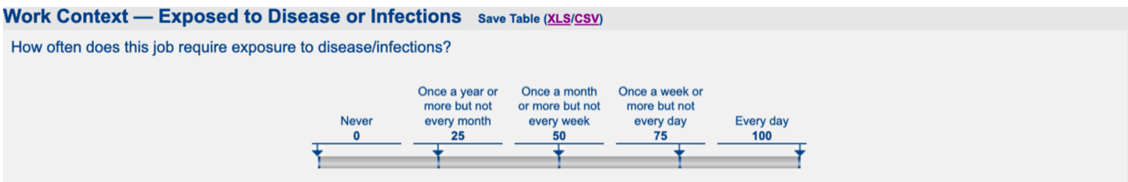
Notes: The map illustrates the cumulative number of (confirmed) COVID-19 cases for each state as of March 15, 2020.

Figure A10: COVID-19 Deaths by State



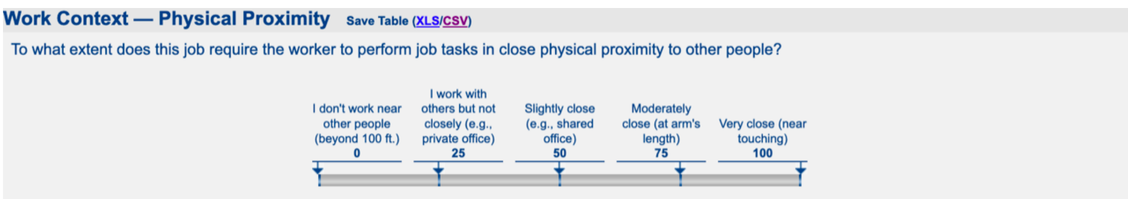
Notes: The map illustrates the number of COVID-19 deaths for each state as of March 15, 2020.

Figure A11: O*NET Survey Question Used for Exposure to Disease



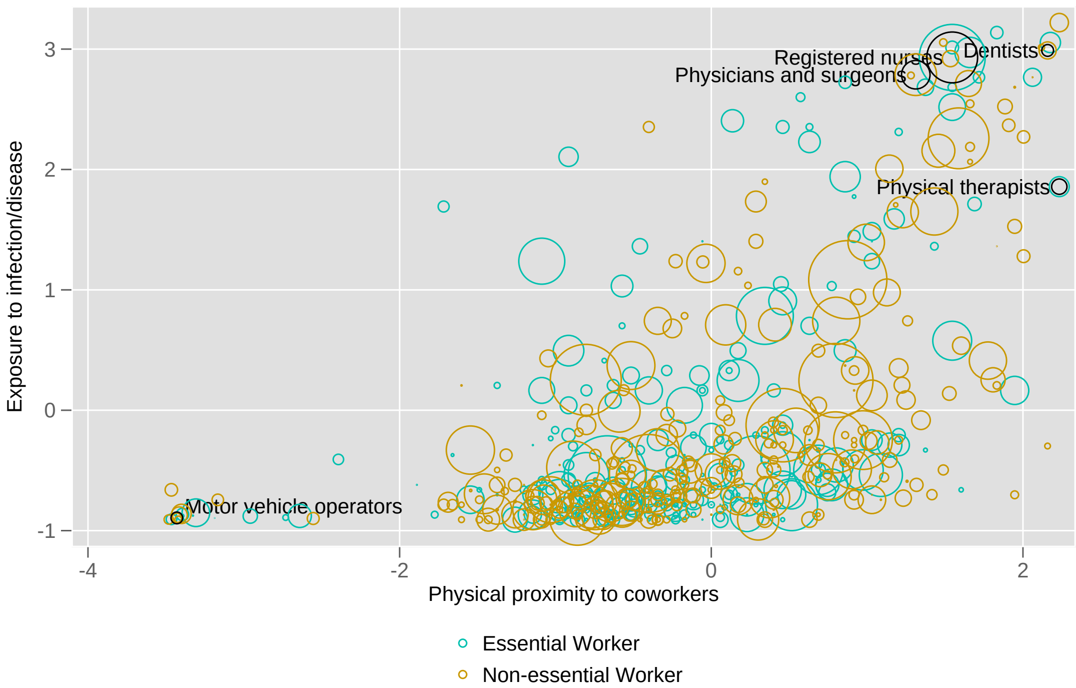
Notes: Survey question asking "How often does this job require exposure to disease/infections?" with five possible answers: (1) Never, (2) Once a year or more but not every month, (3) Once a month or more but not every week, (4) Once a week or more but not every day, and (5) Every day.

Figure A12: O*NET Survey Question Used for Physical Proximity



Notes: Survey question asking "How physically close to other people are you when you perform your current job?" with five possible responses: (1) I don't work near other people(beyond 100 ft.), (2) I work with others but not closely (e.g., private office), (3) Slightly close (e.g., shared office), (4) Moderately close(at arm's length), and (5) Very close (near touching).

Figure A13: Physical Proximity, Exposure to the Disease and Essential Workers by Occupation

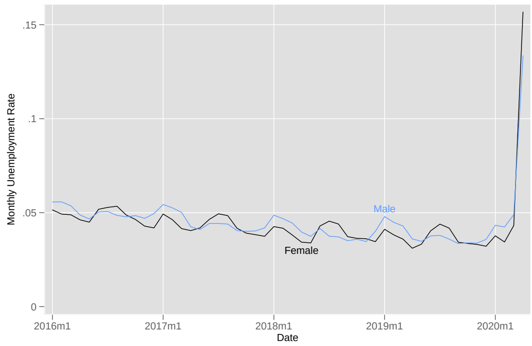


Notes: Each circle represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's physical proximity to coworkers, measured by O*NET's index. The further to the right, the closer in proximity employees in that occupation work with their coworkers. The y-axis plots each occupation's exposure to infection and disease, also measured by O*NET's index. The further up, the more frequently employees in that occupation are exposes to infection and disease. The color of the circles corresponds to whether or not the occupation is considered essential by the Labor Market Information Institute.

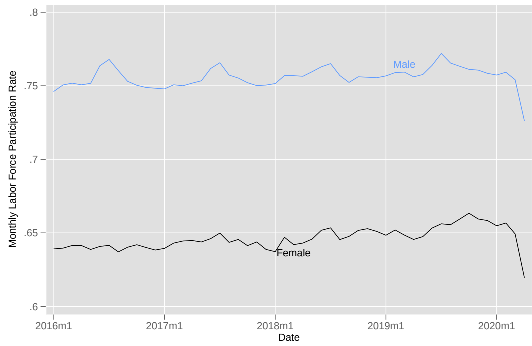
Figure A14: Remote Work, Exposure to the Disease and Essential Workers by Occupation

Notes: Each circle represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's ability to work remotely. The further to the right, the more easily that occupation can be done remotely. The y-axis plots each occupation's exposure to infection and disease, also measured by O*NET's index. The further up, the more frequently employees in that occupation are exposes to infection and disease. The color of the circles corresponds to whether or not the occupation is considered essential by the Labor Market Information Institute.

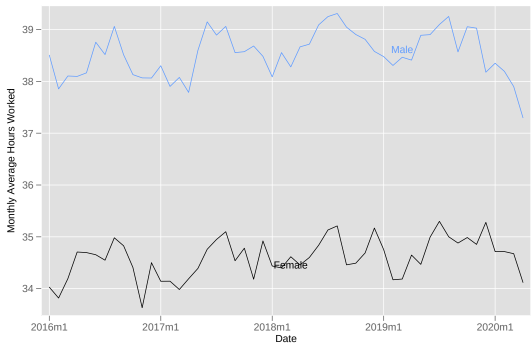
Figure A15: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Gender.



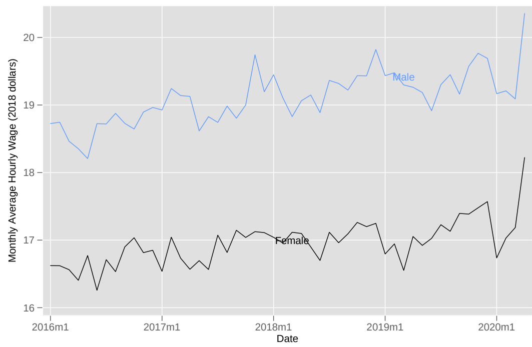
(a) Unemployment Rate.



(b) Labor Force Participation.



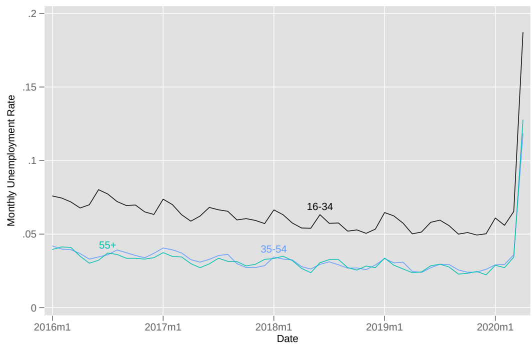
(c) Hours of Work.



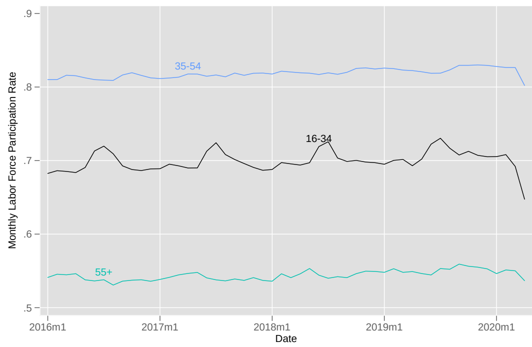
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by gender. Panel B plots the labor force participation by gender. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by gender. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by gender. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

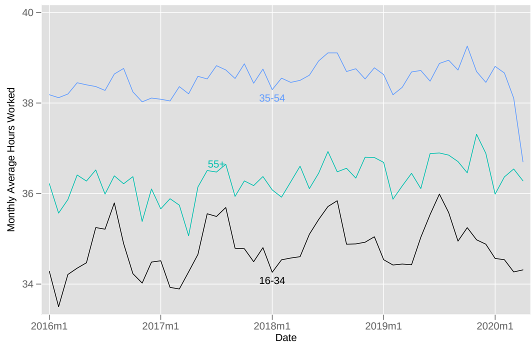
Figure A16: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Age Groups.



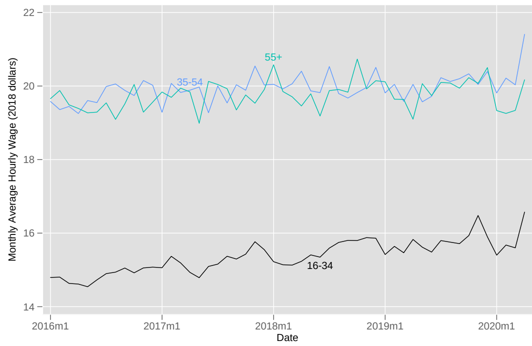
(a) Unemployment Rate.



(b) Labor Force Participation.



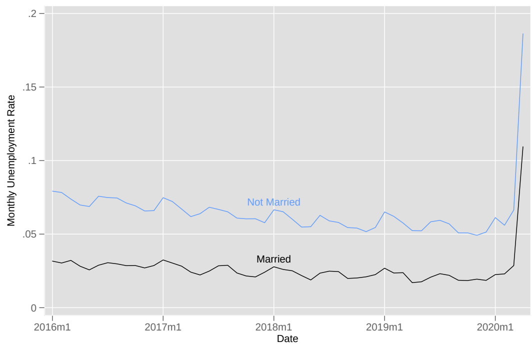
(c) Hours of Work.



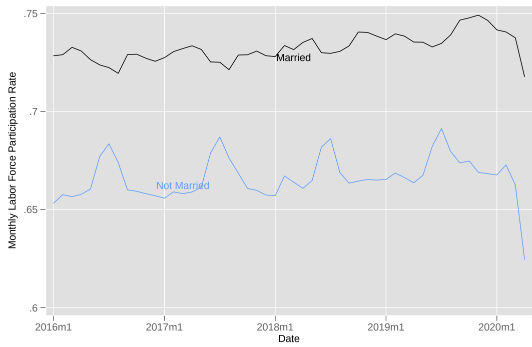
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by age groups. Panel B plots the labor force participation by age groups. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by age groups. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by age groups. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

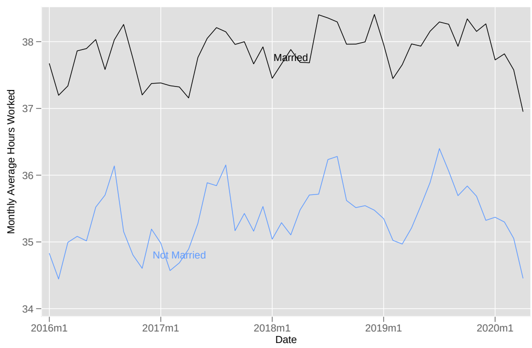
Figure A17: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Marital Status.



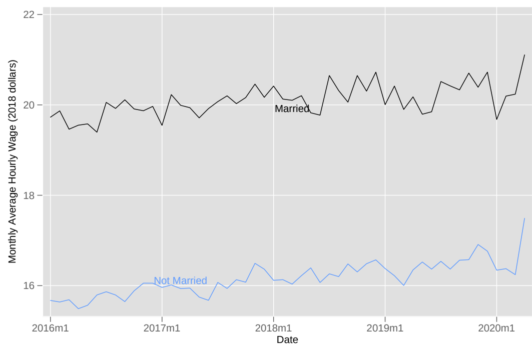
(a) Unemployment Rate.



(b) Labor Force Participation.



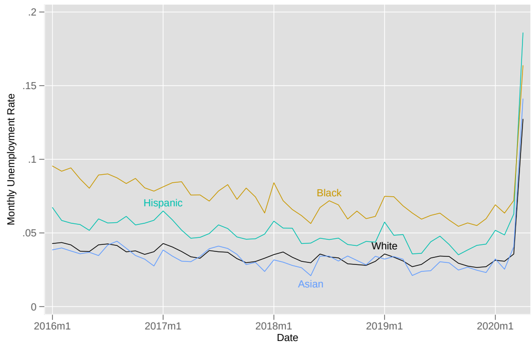
(c) Hours of Work.



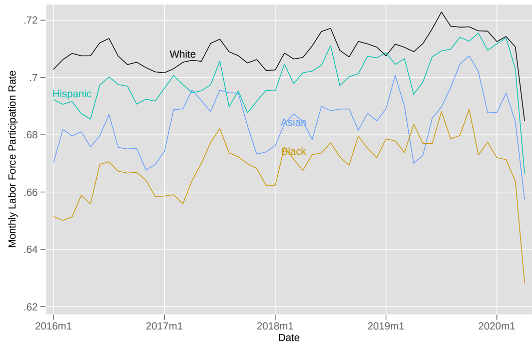
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by marital status. Panel B plots the labor force participation by marital status. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by marital status. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by marital status. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

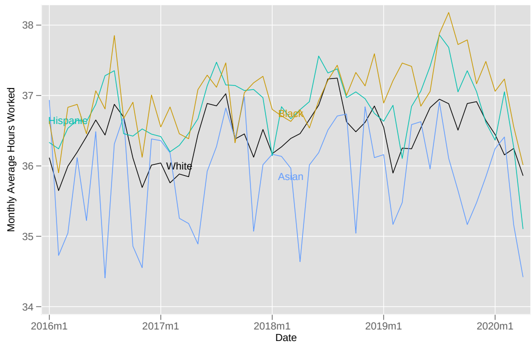
Figure A18: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Race.



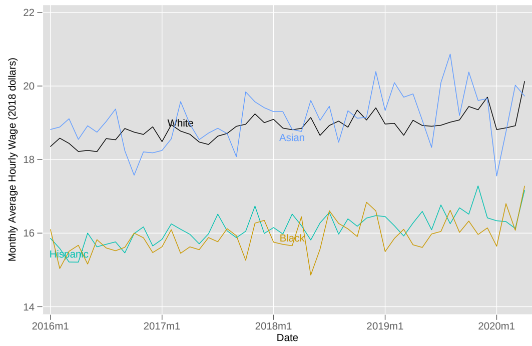
(a) Unemployment Rate.



(b) Labor Force Participation.



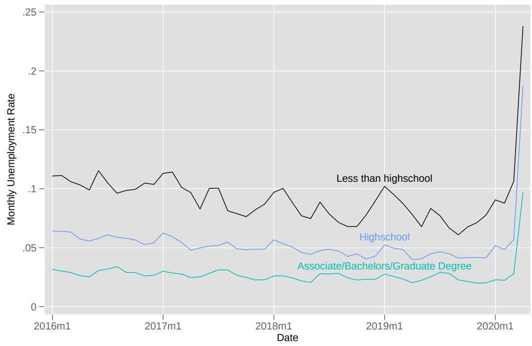
(c) Hours of Work.



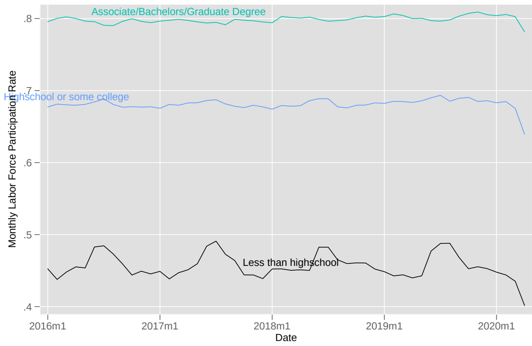
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by race. Panel B plots the labor force participation by race. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by race. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by race. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

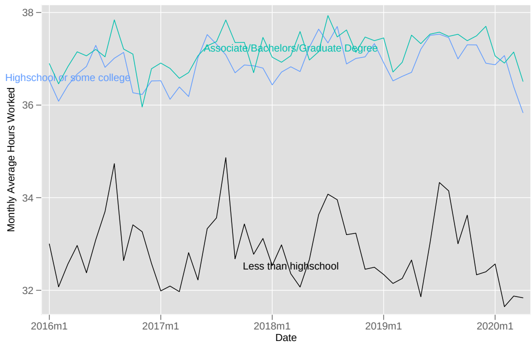
Figure A19: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Education Status.



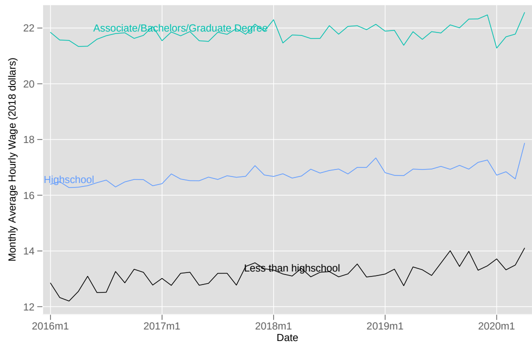
(a) Unemployment Rate.



(b) Labor Force Participation.



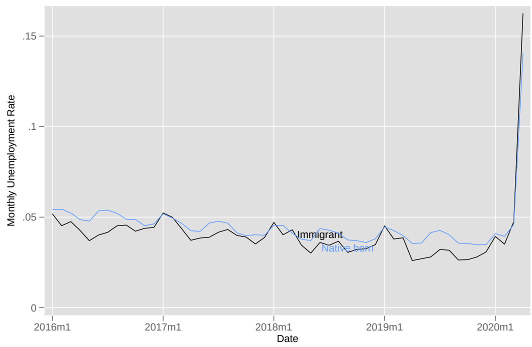
(c) Hours of Work.



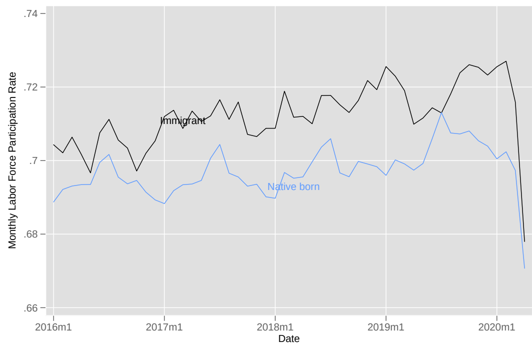
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by education status. Panel B plots the labor force participation by education status. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by education status. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by education status. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

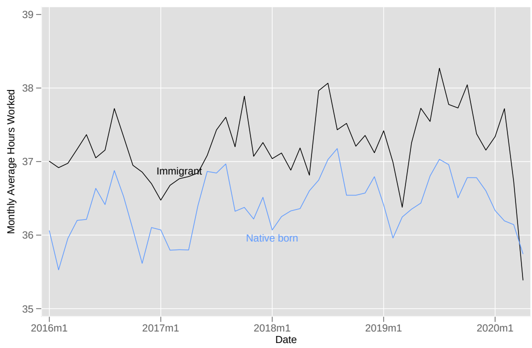
Figure A20: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Immigration Status.



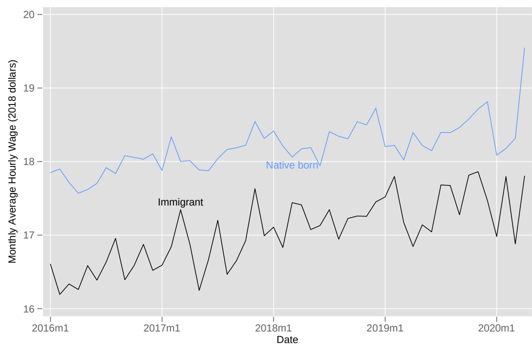
(a) Unemployment Rate.



(b) Labor Force Participation.



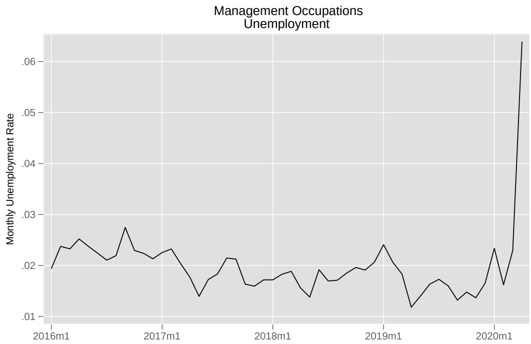
(c) Hours of Work.



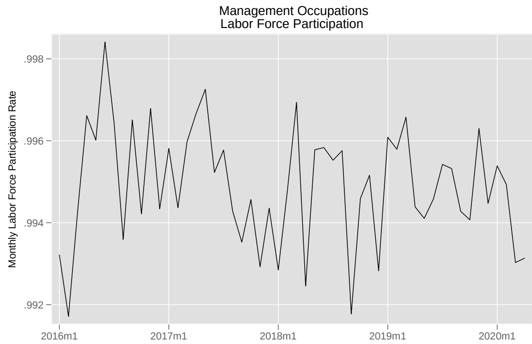
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by immigration status. Panel B plots the labor force participation by immigration status. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by immigration status. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by immigration status. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

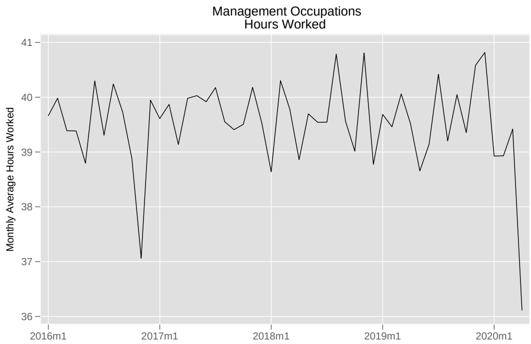
Figure A21: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Management Occupations.



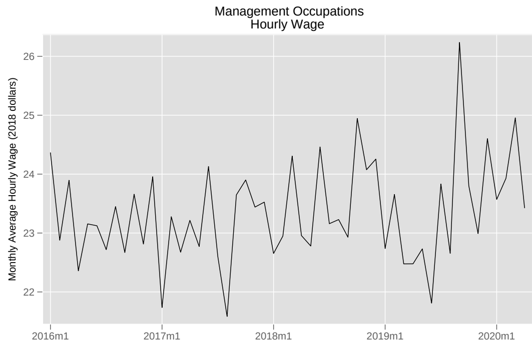
(a) Unemployment Rate.



(b) Labor Force Participation.



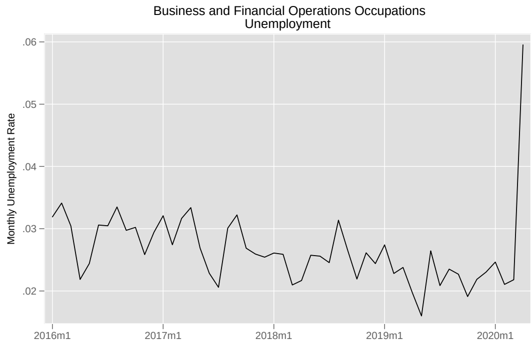
(c) Hours of Work.



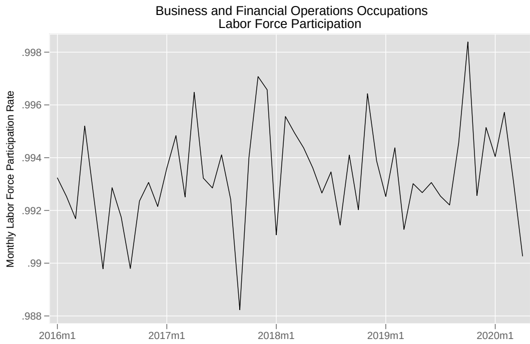
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

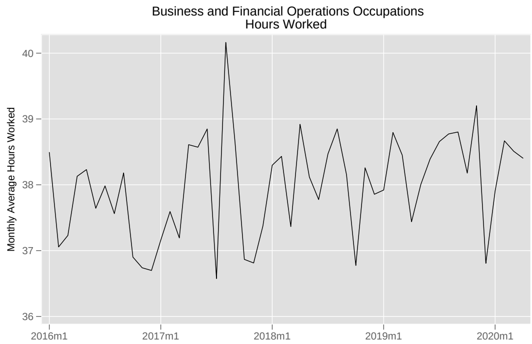
Figure A22: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Business and Financial Operations Occupations".



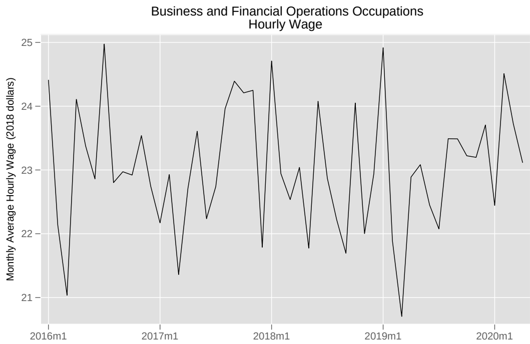
(a) Unemployment Rate.



(b) Labor Force Participation.



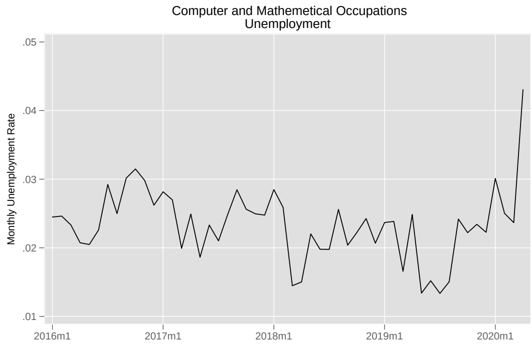
(c) Hours of Work.



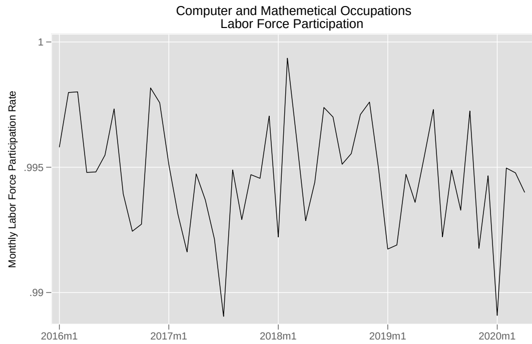
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

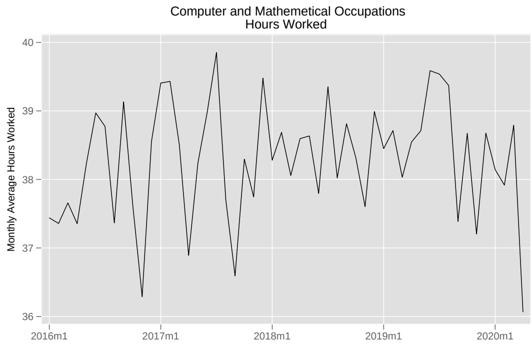
Figure A23: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Computer and Mathemetical Occupations.



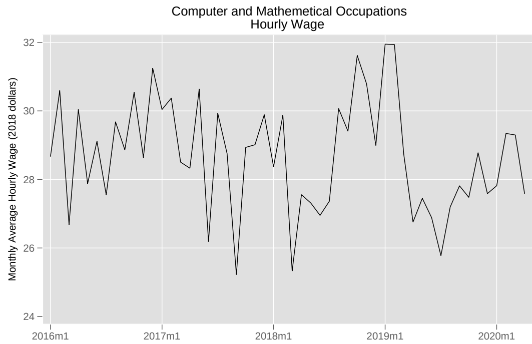
(a) Unemployment Rate.



(b) Labor Force Participation.



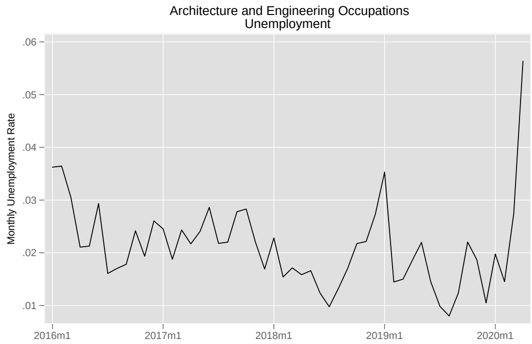
(c) Hours of Work.



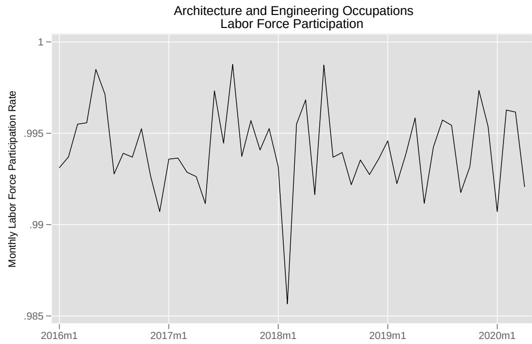
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

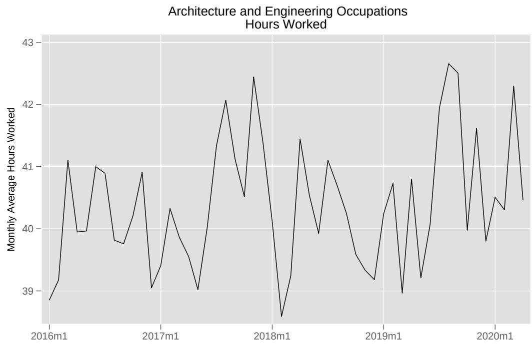
Figure A24: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Architecture and Engineering Occupations.



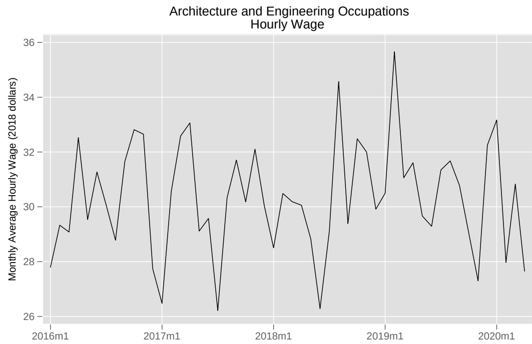
(a) Unemployment Rate.



(b) Labor Force Participation.



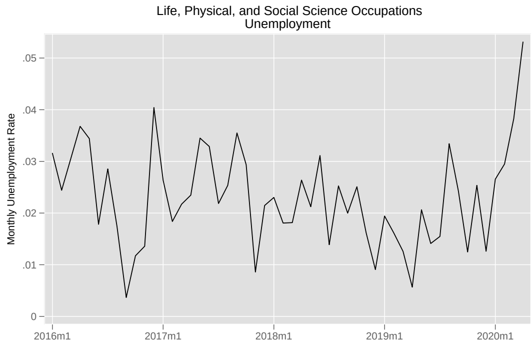
(c) Hours of Work.



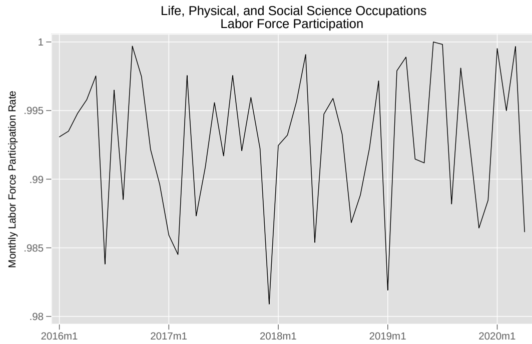
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

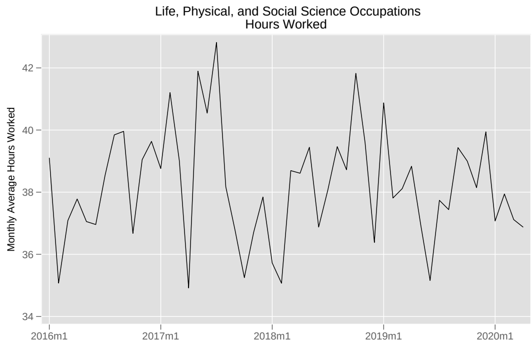
Figure A25: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Life, Physical, and Social Science Occupations.



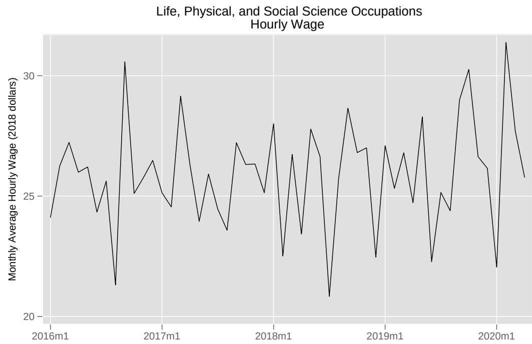
(a) Unemployment Rate.



(b) Labor Force Participation.



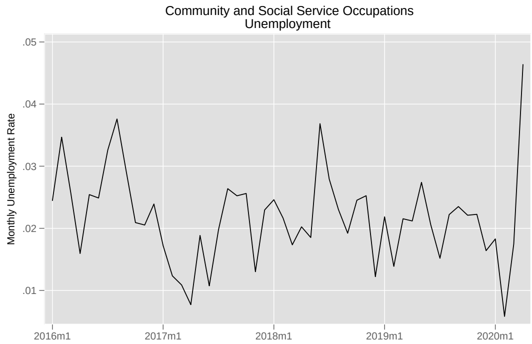
(c) Hours of Work.



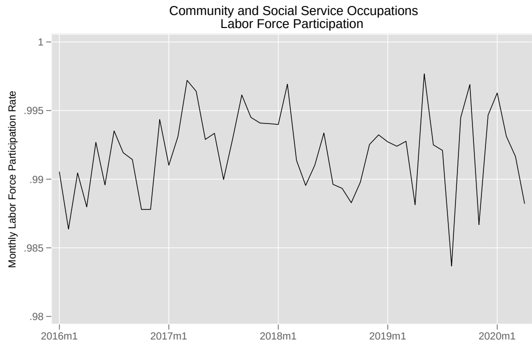
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

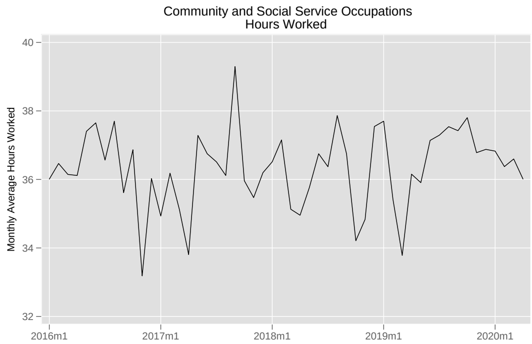
Figure A26: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Community and Social Service Occupations.



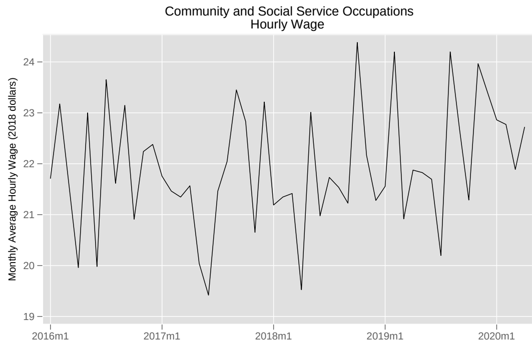
(a) Unemployment Rate.



(b) Labor Force Participation.



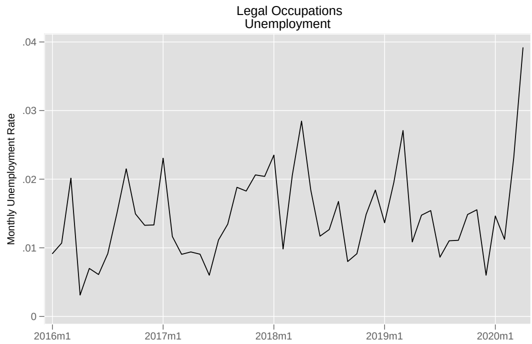
(c) Hours of Work.



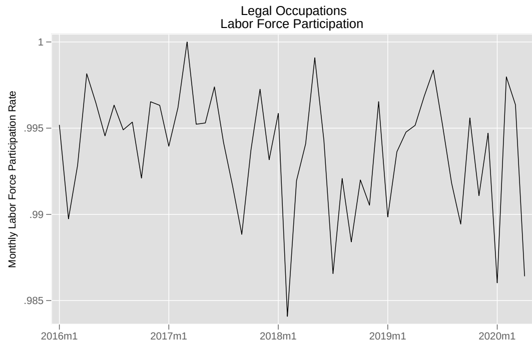
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

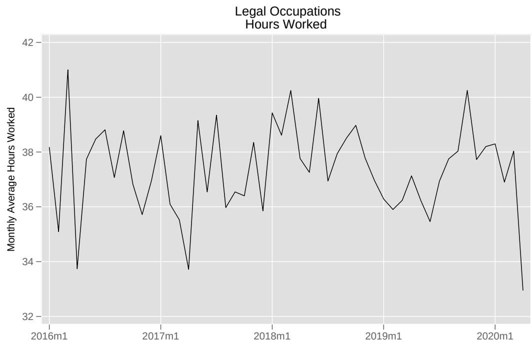
Figure A27: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Legal Occupations.



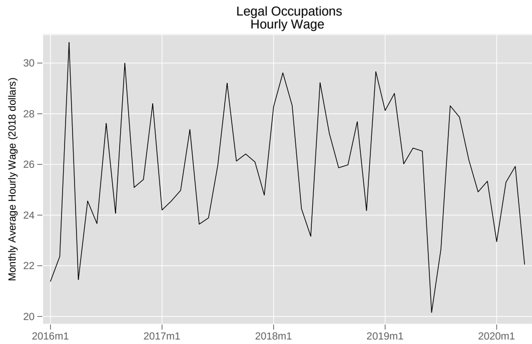
(a) Unemployment Rate.



(b) Labor Force Participation.



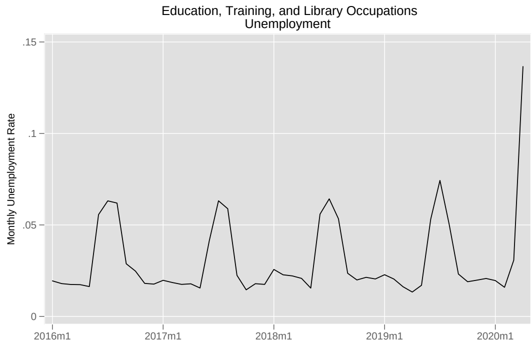
(c) Hours of Work.



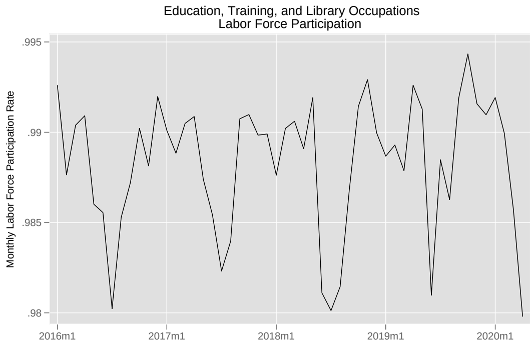
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

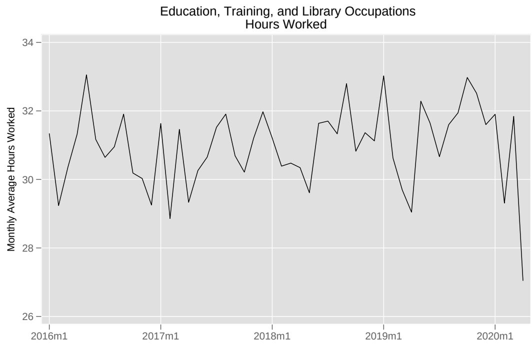
Figure A28: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Education, Training, and Library Occupations.



(a) Unemployment Rate.



(b) Labor Force Participation.

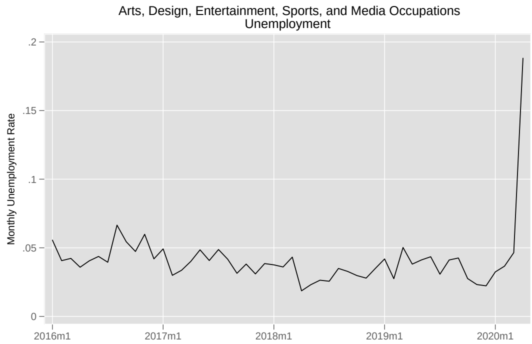


(c) Hours of Work.

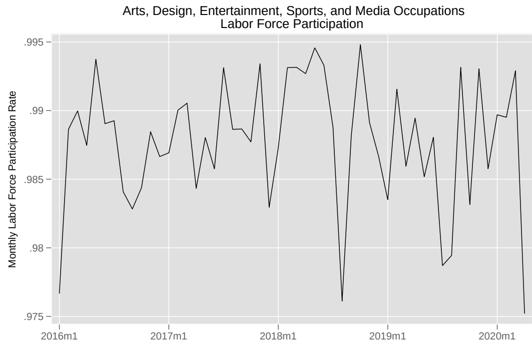
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

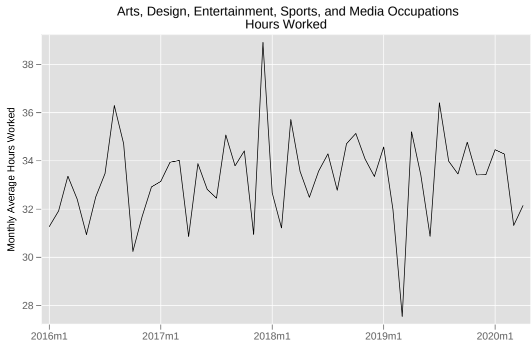
Figure A29: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Arts, Design, Entertainment, Sports, and Media Occupations.



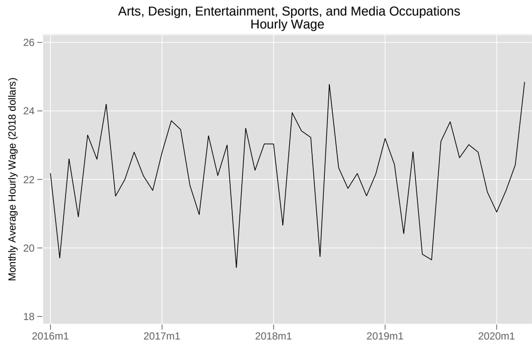
(a) Unemployment Rate.



(b) Labor Force Participation.



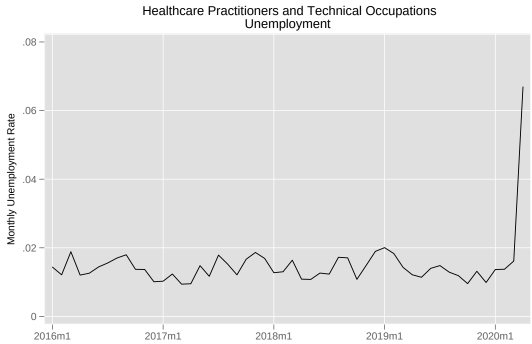
(c) Hours of Work.



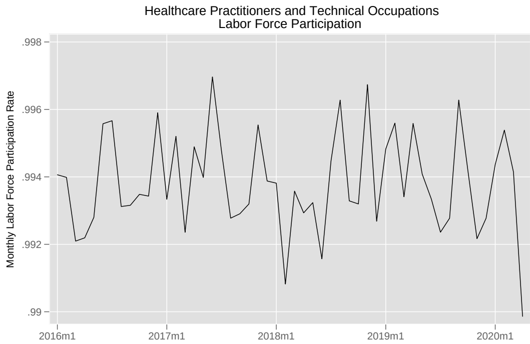
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

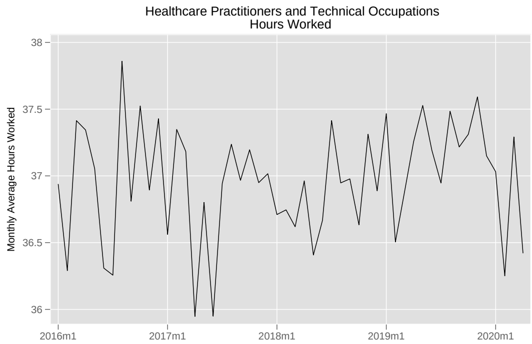
Figure A30: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Healthcare Practitioners and Technical Occupations.



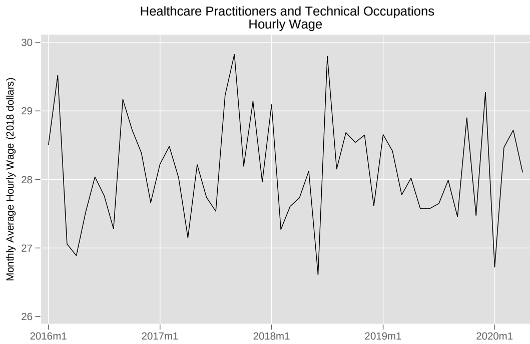
(a) Unemployment Rate.



(b) Labor Force Participation.



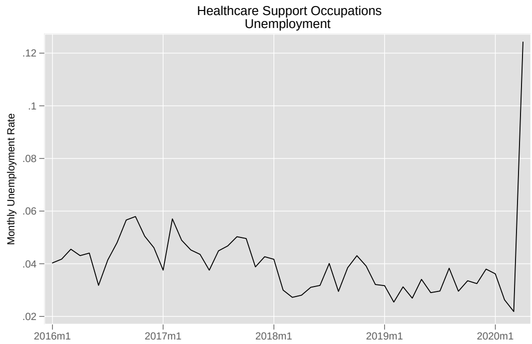
(c) Hours of Work.



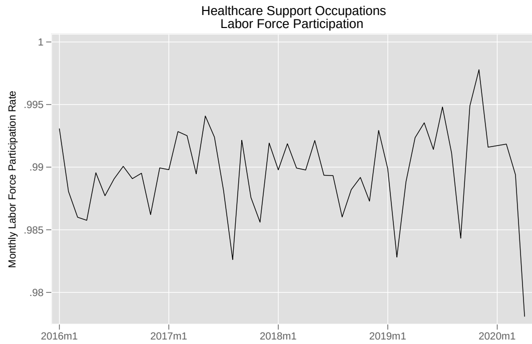
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

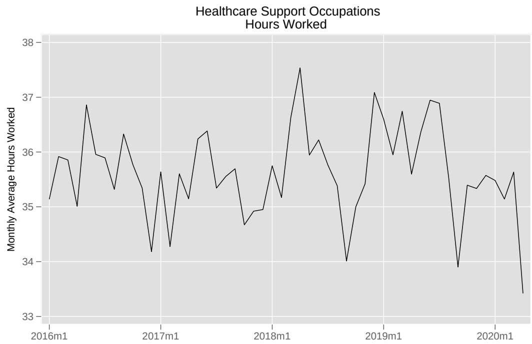
Figure A31: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Healthcare Support Occupations.



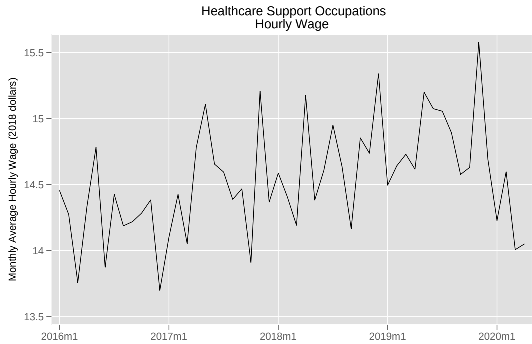
(a) Unemployment Rate.



(b) Labor Force Participation.



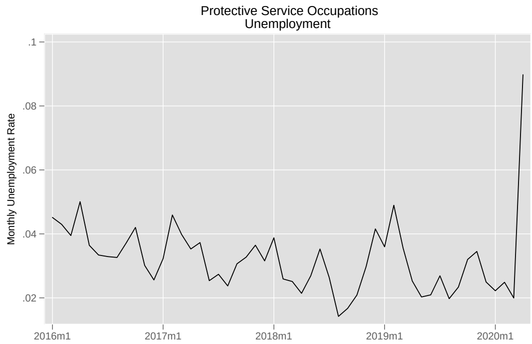
(c) Hours of Work.



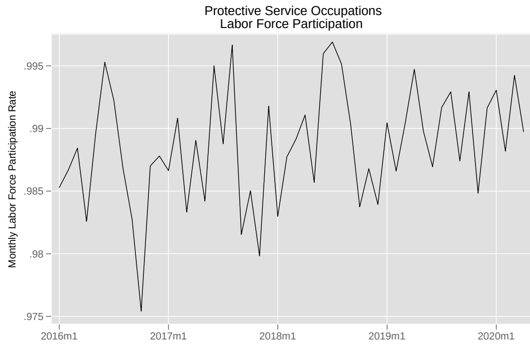
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

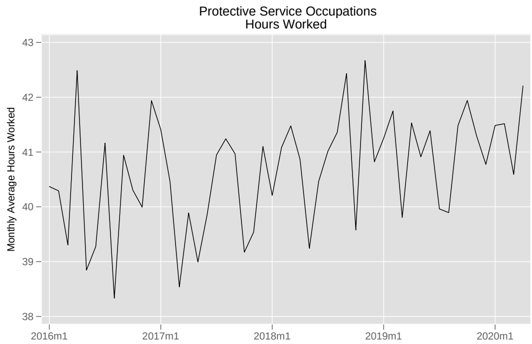
Figure A32: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Protective Service Occupations.



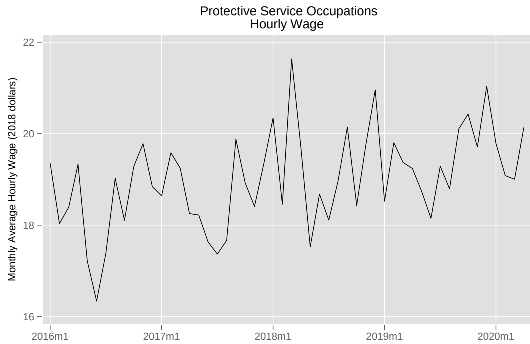
(a) Unemployment Rate.



(b) Labor Force Participation.



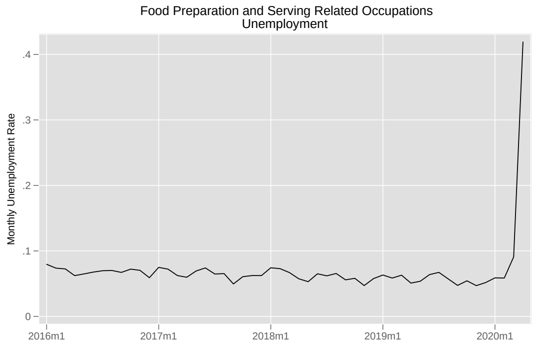
(c) Hours of Work.



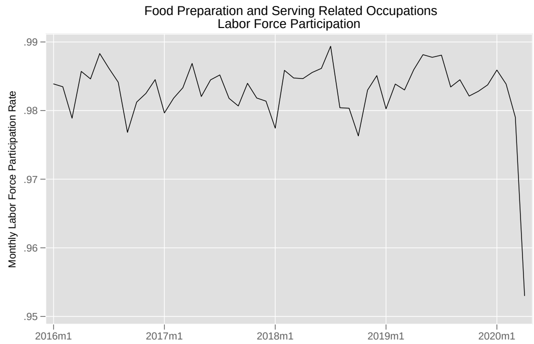
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

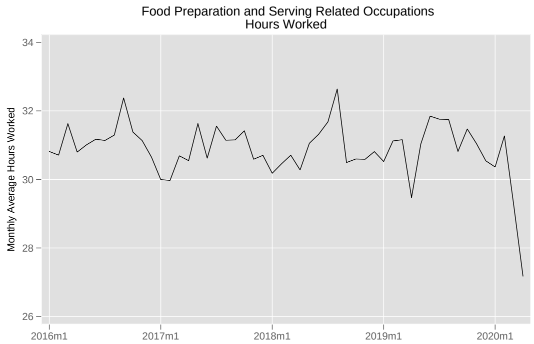
Figure A33: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Food Preparation and Serving Related Occupations.



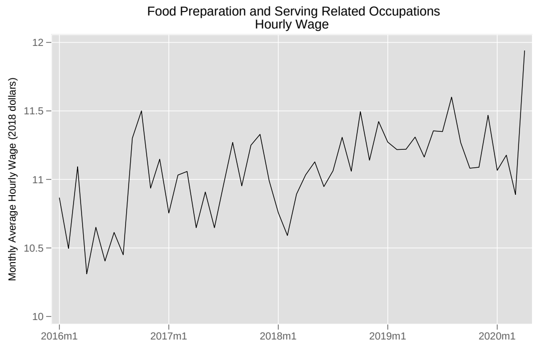
(a) Unemployment Rate.



(b) Labor Force Participation.



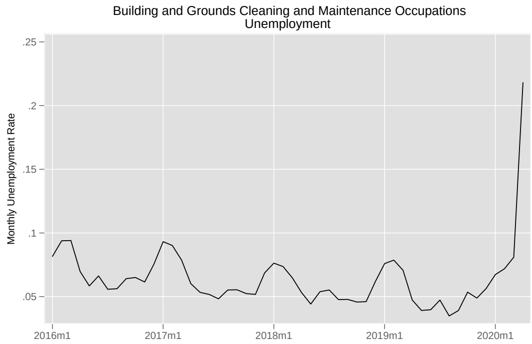
(c) Hours of Work.



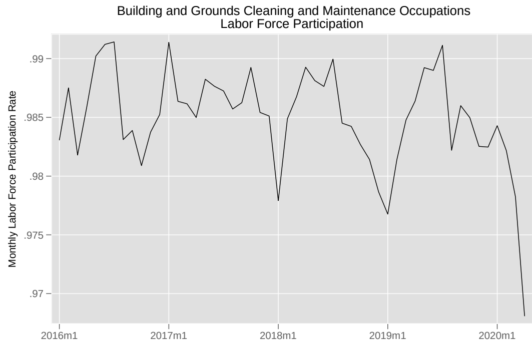
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

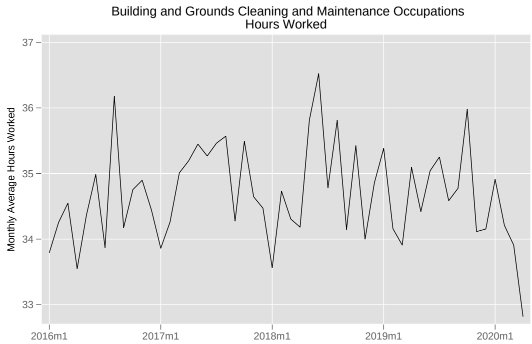
Figure A34: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Building and Grounds Cleaning and Maintenance Occupations.



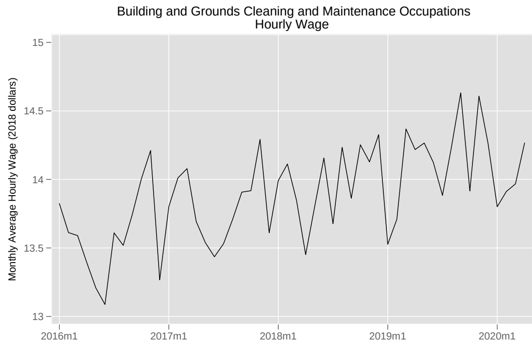
(a) Unemployment Rate.



(b) Labor Force Participation.



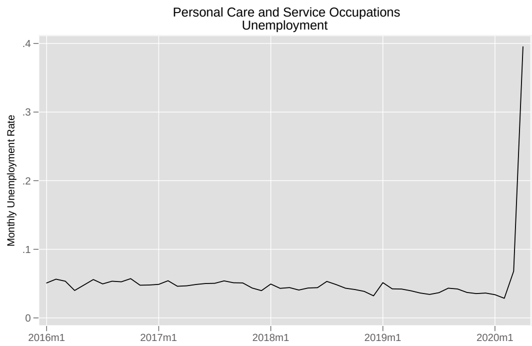
(c) Hours of Work.



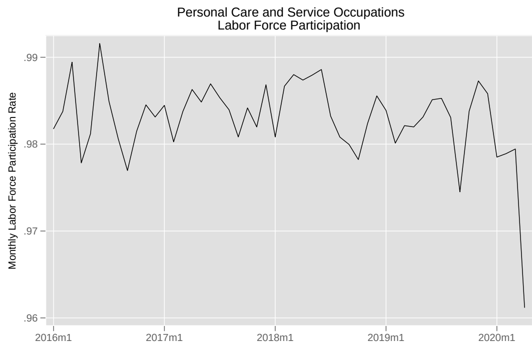
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

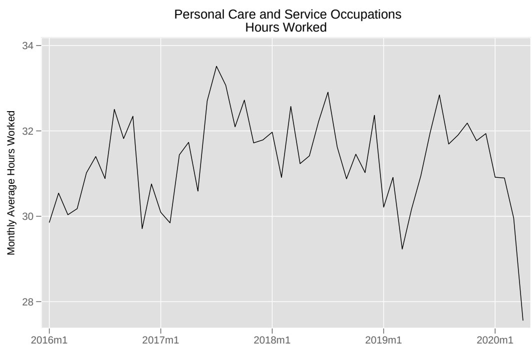
Figure A35: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Personal Care and Service Occupations.



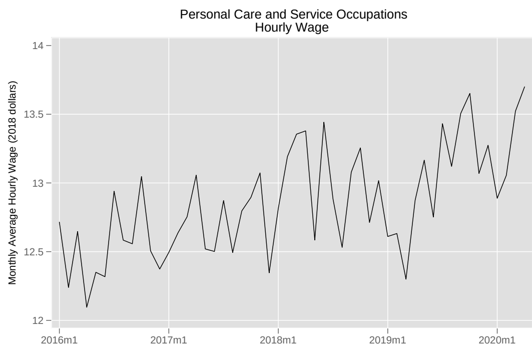
(a) Unemployment Rate.



(b) Labor Force Participation.



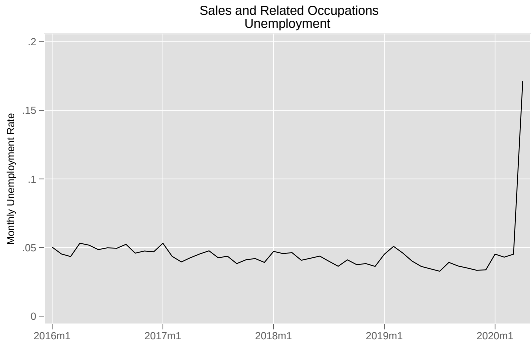
(c) Hours of Work.



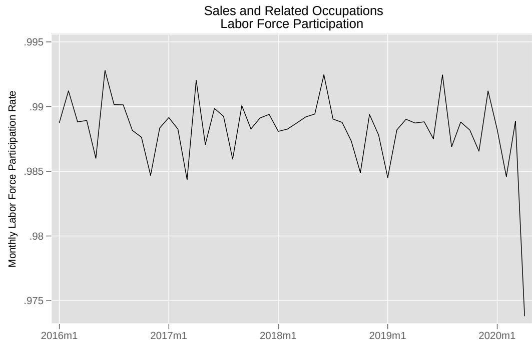
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

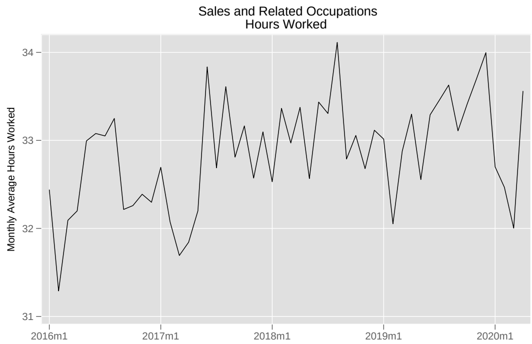
Figure A36: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Sales and Related Occupations.



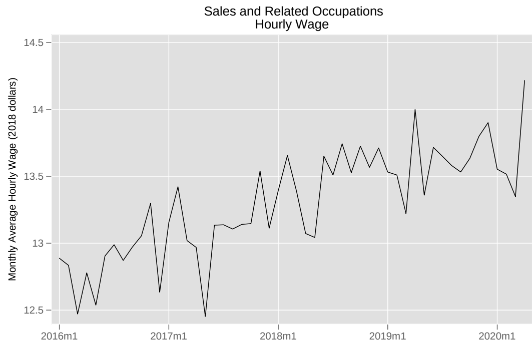
(a) Unemployment Rate.



(b) Labor Force Participation.



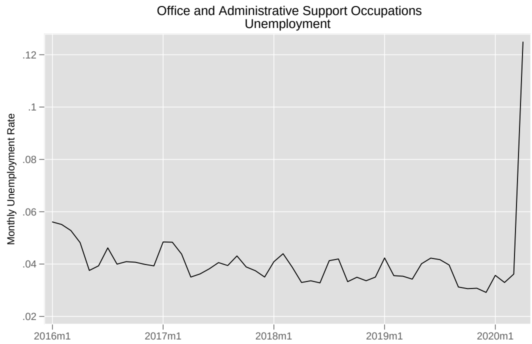
(c) Hours of Work.



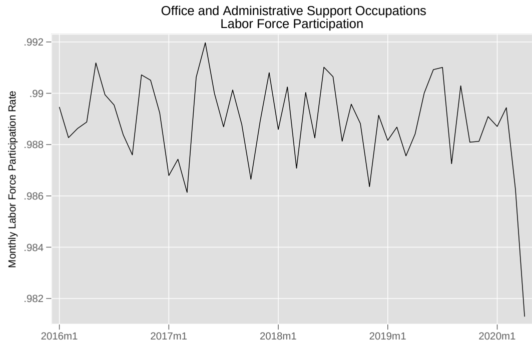
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

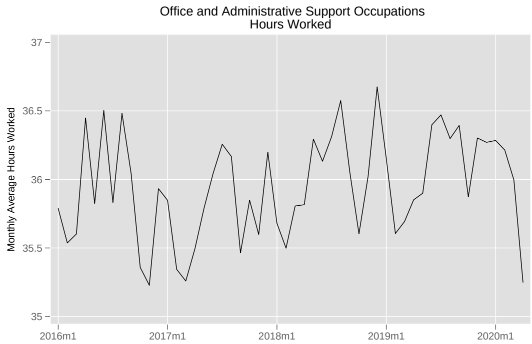
Figure A37: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Office and Administrative Support Occupations.



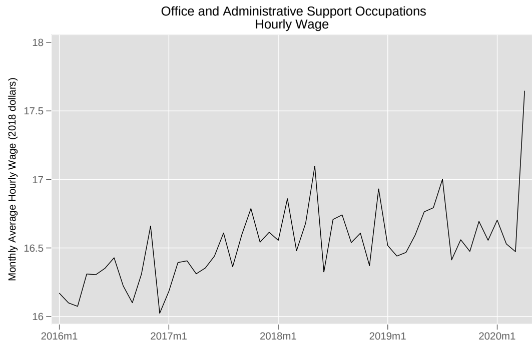
(a) Unemployment Rate.



(b) Labor Force Participation.



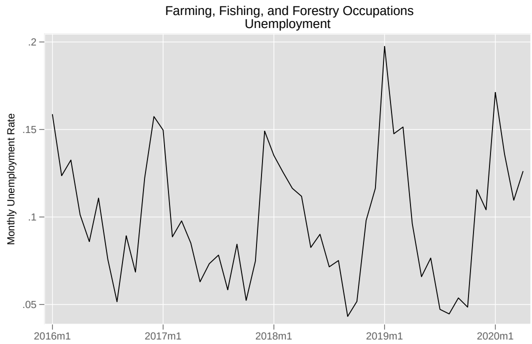
(c) Hours of Work.



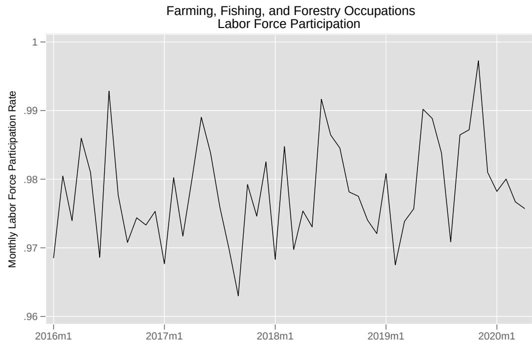
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

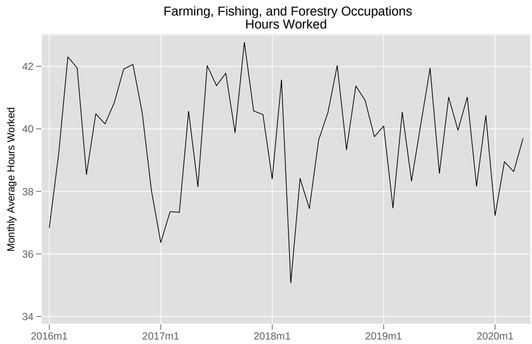
Figure A38: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Farming, Fishing, and Forestry Occupations.



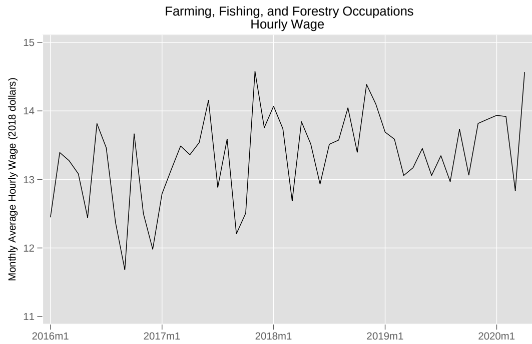
(a) Unemployment Rate.



(b) Labor Force Participation.



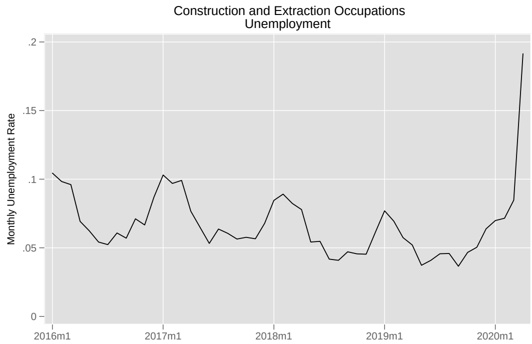
(c) Hours of Work.



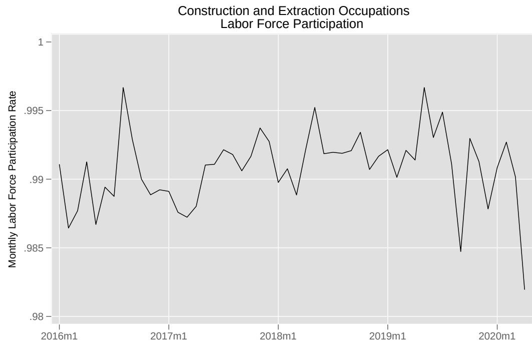
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

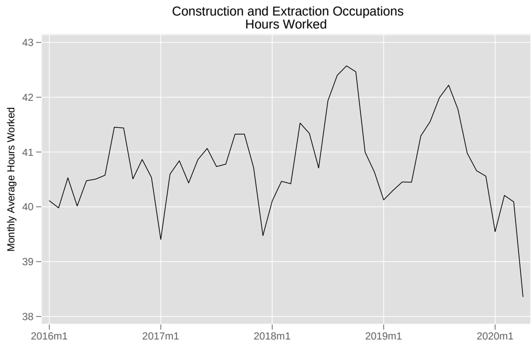
Figure A39: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Construction and Extraction Occupations.



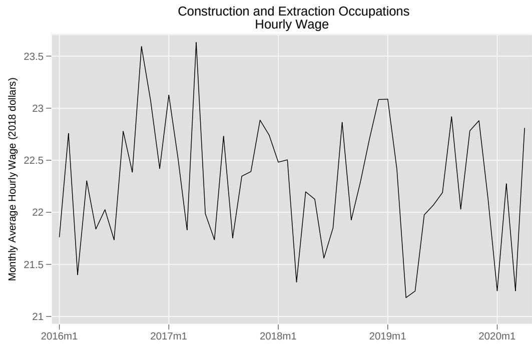
(a) Unemployment Rate.



(b) Labor Force Participation.



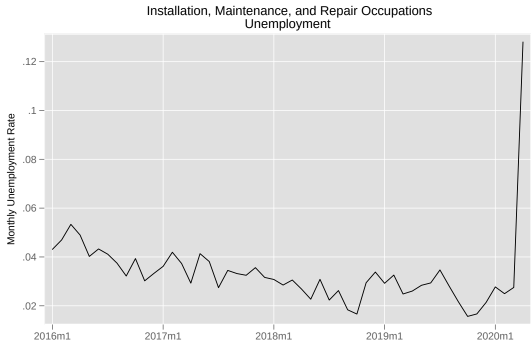
(c) Hours of Work.



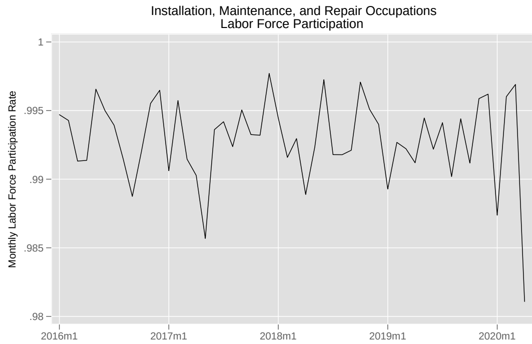
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

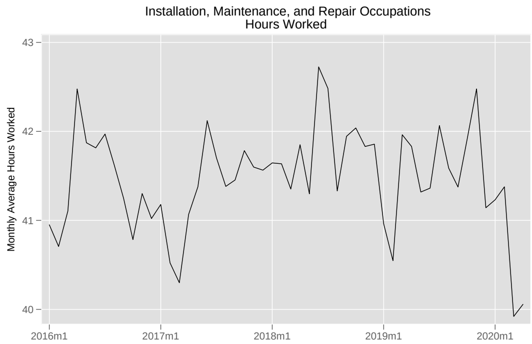
Figure A40: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Installation, Maintenance, and Repair Occupations.



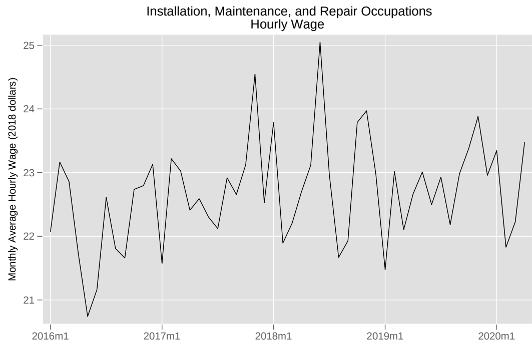
(a) Unemployment Rate.



(b) Labor Force Participation.



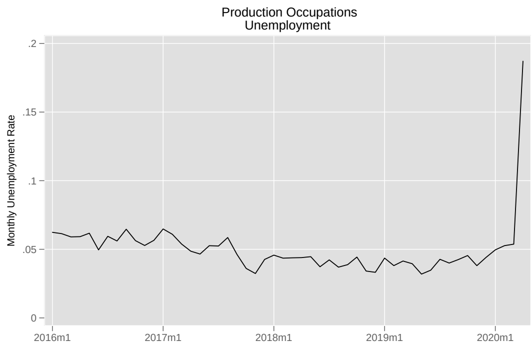
(c) Hours of Work.



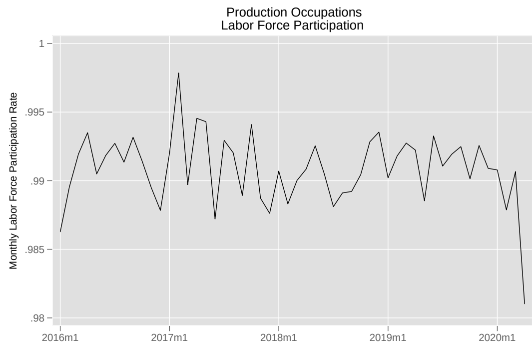
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

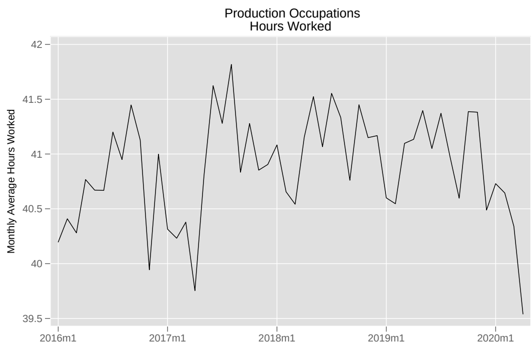
Figure A41: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Production Occupations.



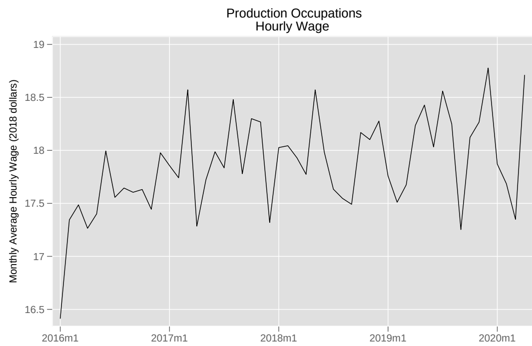
(a) Unemployment Rate.



(b) Labor Force Participation.



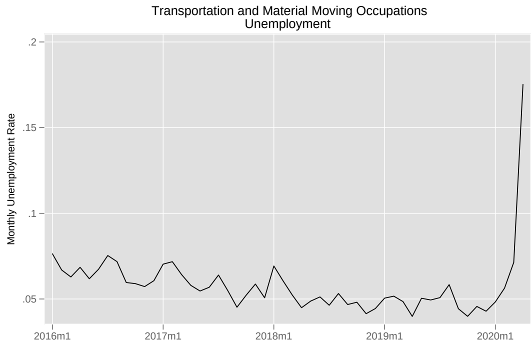
(c) Hours of Work.



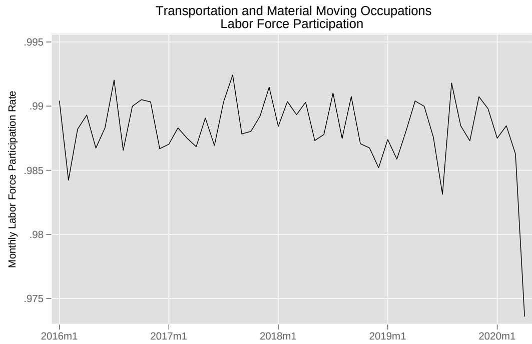
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

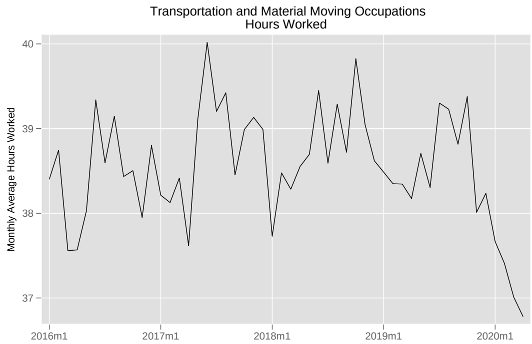
Figure A42: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Transportation and Material Moving Occupations.



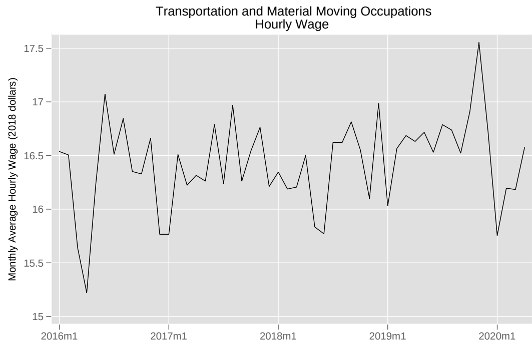
(a) Unemployment Rate.



(b) Labor Force Participation.



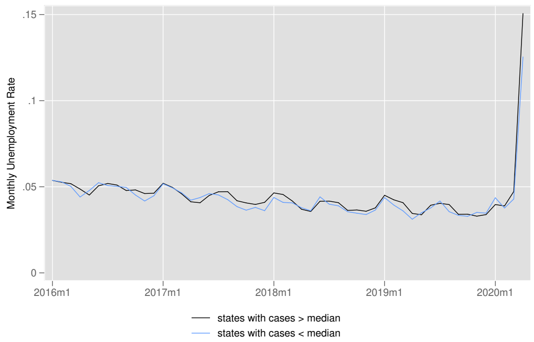
(c) Hours of Work.



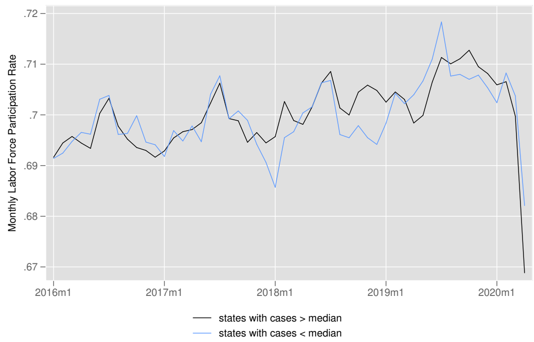
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

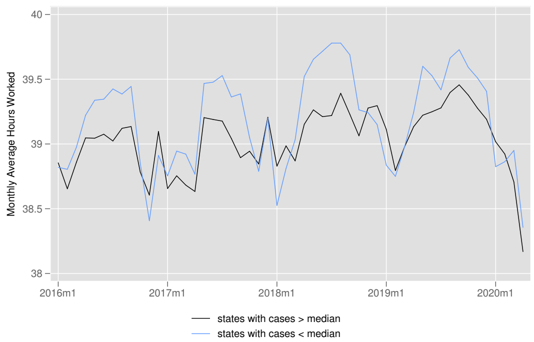
Figure A43: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by State COVID-19 Case Rate.



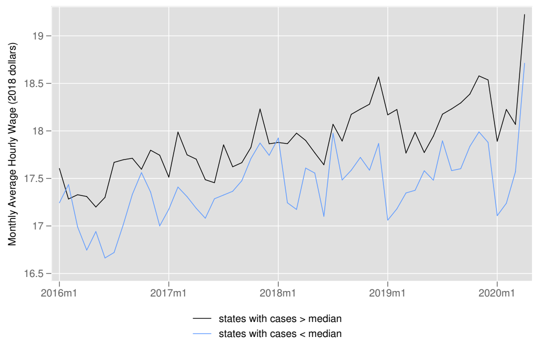
(a) Unemployment Rate.



(b) Labor Force Participation.



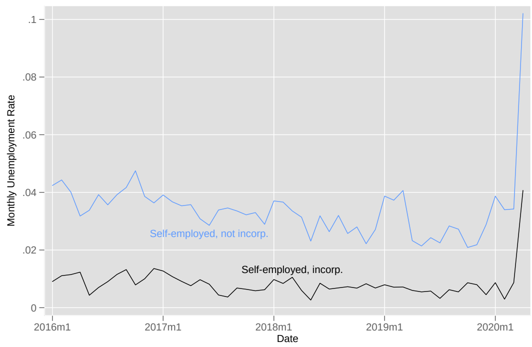
(c) Hours of Work.



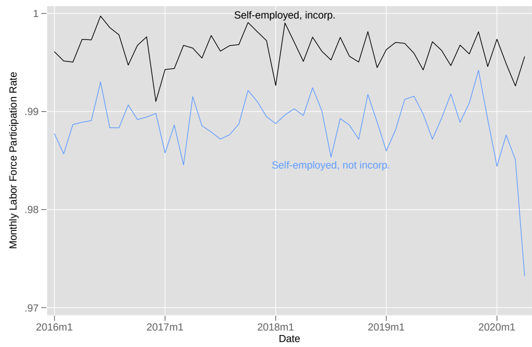
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate in states above and below the April 2020 median for cumulative number of known COVID-19 cases per 10,000 inhabitants. Panel B plots the labor force participation in states above and below the April 2020 median for cumulative number of known COVID-19 cases per 10,000 inhabitants. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work in states above and below the April 2020 median for cumulative number of known COVID-19 cases per 10,000 inhabitants. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages in states above and below the April 2020 median for cumulative number of known COVID-19 cases per 10,000 inhabitants. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

Figure A44: Unemployment Rate, Labor Force Participation, and Hours of Work by Self-Employment Incorporated and Unincorporated.



(a) Unemployment Rate.

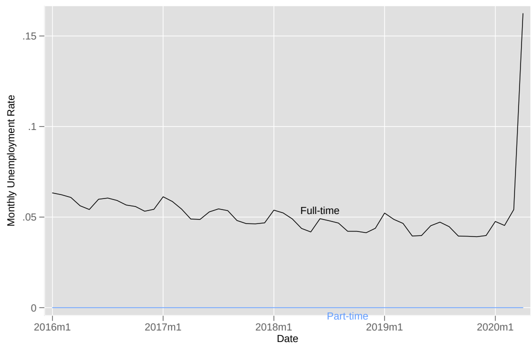


(b) Labor Force Participation.

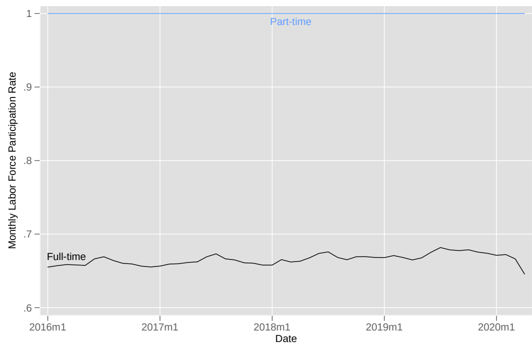
(c) Hours of Work.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for self-employed individuals, incorporated and self-employed individuals, unincorporated. Panel B plots the labor force participation. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile.

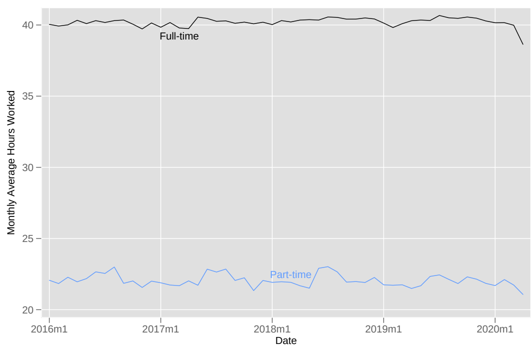
Figure A45: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Full-Time and Part-Time Workers.



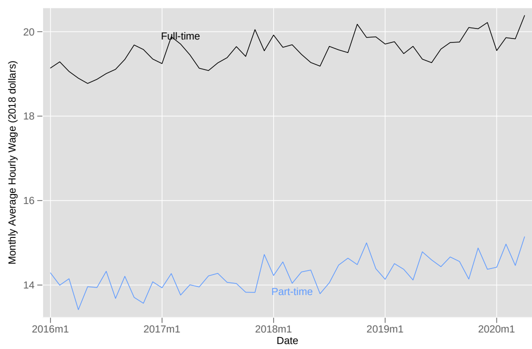
(a) Unemployment Rate.



(b) Labor Force Participation.



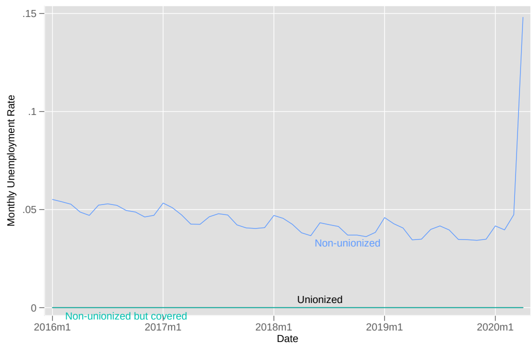
(c) Hours of Work.



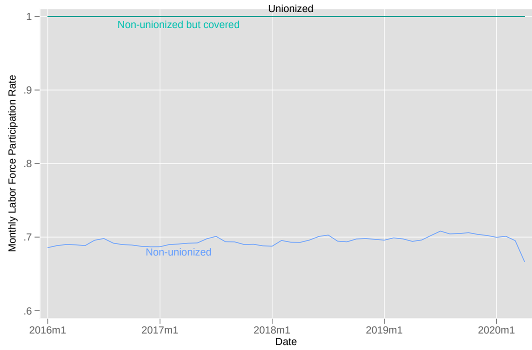
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate for full-time and part-time workers. Panel B plots the labor force participation for full-time and part-time workers. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work for full-time and part-time workers. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages for full-time and part-time workers. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

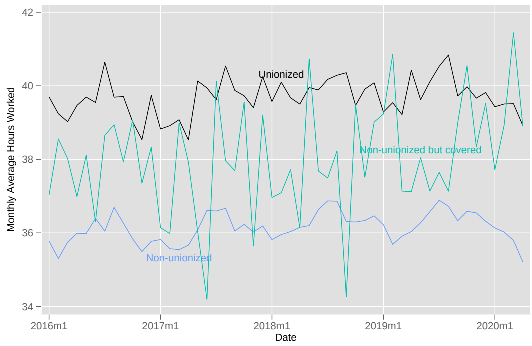
Figure A46: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Union Status.



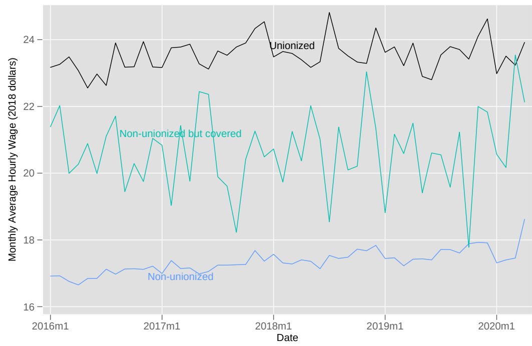
(a) Unemployment Rate.



(b) Labor Force Participation.



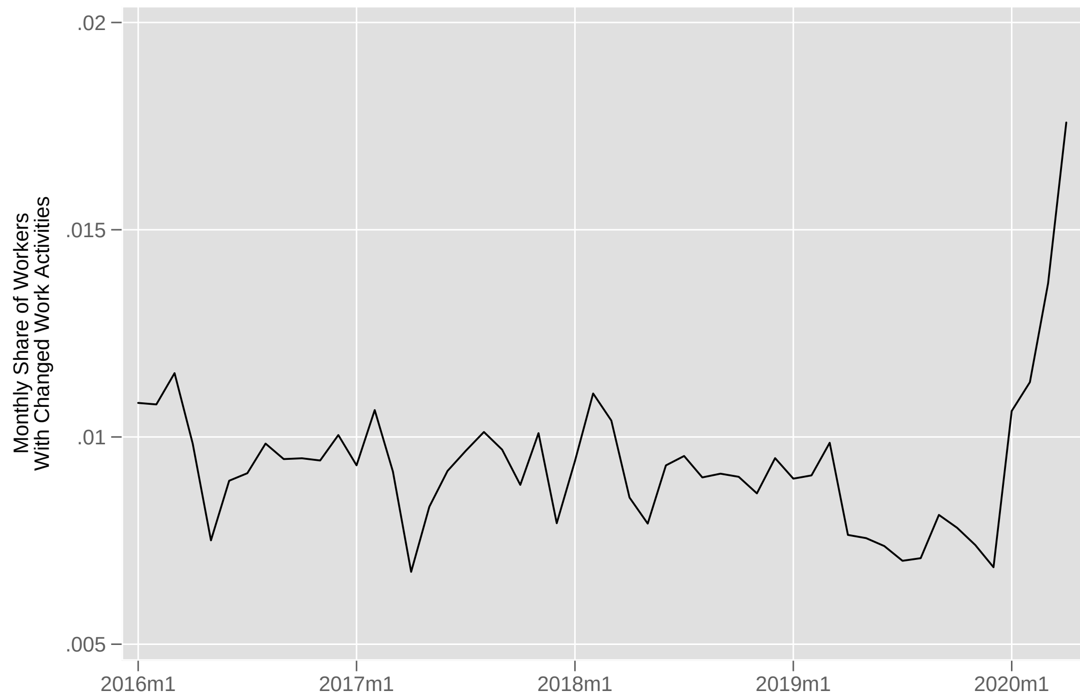
(c) Hours of Work.



(d) Hourly Wages.

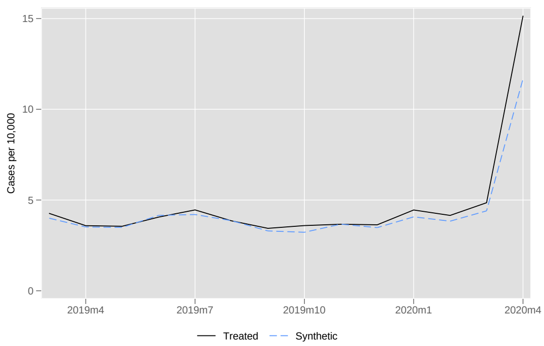
Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to April 2020. Panel A plots the unemployment rate by union status. Panel B plots the labor force participation by union status. Individuals in the labor force were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. Panel C plots hours work by union status. Hours work: civilians aged 16–70 who are employed and either at work or absent from work during the survey week, all jobs. Trimmed to exclude values below 1st percentile and above 99th percentile. Panel D plots hourly wages by union status. Hourly wages: civilians aged 16–70 currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. Excludes self-employed persons. Trimmed to exclude values below 1st percentile and above 99th percentile. Reported in 2018 constant dollars.

Figure A47: COVID-19 and Work Arrangement

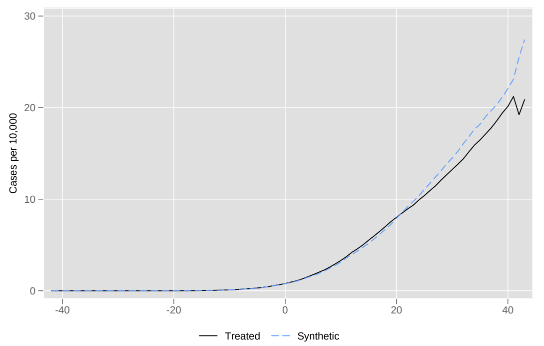


Notes: The y-axis plots the share of respondents who answered ”Yes” to the question ”Have the usual activities and duties of your job changed since last month?”

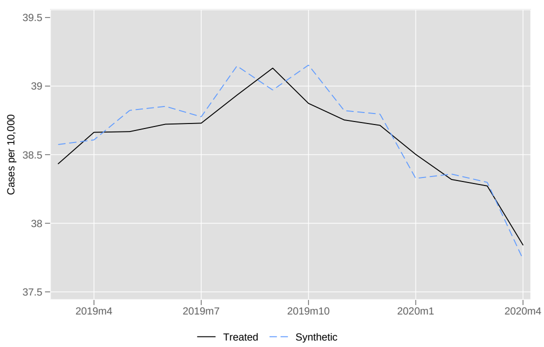
Figure A48: Synthetic Control Method Summary: Effect of Stay Home Order on Unemployment Rate, Case Rate, Death Rate (weighted, trimmed)



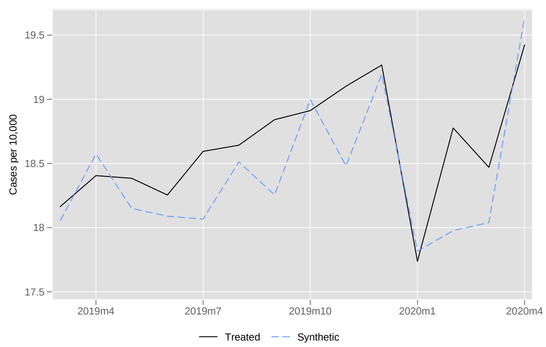
(a) Unemployment Rate.



(b) Case per 10,000.



(c) Hours of Work.



(d) Hourly Wages.

Table A1: Date First COVID-19 Confirmed Case and Death

State	**Date First Confirmed Case** (1)	**Date First Death** (2)
Alabama	13-Mar-2020	25-Mar-2020
Alaska	07-Mar-2020	25-Mar-2020
Arizona	26-Jan-2020	20-Mar-2020
Arkansas	11-Mar-2020	24-Mar-2020
California	25-Jan-2020	04-Mar-2020
Colorado	05-Mar-2020	13-Mar-2020
Connecticut	01-Mar-2020	21-Mar-2020
Delaware	11-Mar-2020	26-Mar-2020
District of Columbia	07-Mar-2020	20-Mar-2020
Florida	01-Mar-2020	06-Mar-2020
Georgia	02-Mar-2020	12-Mar-2020
Idaho	13-Mar-2020	26-Mar-2020
Illinois	24-Jan-2020	17-Mar-2020
Indiana	06-Mar-2020	16-Mar-2020
Iowa	08-Mar-2020	24-Mar-2020
Kansas	07-Mar-2020	12-Mar-2020
Kentucky	06-Mar-2020	16-Mar-2020
Louisiana	09-Mar-2020	14-Mar-2020
Maine	12-Mar-2020	27-Mar-2020
Maryland	05-Mar-2020	18-Mar-2020
Massachusetts	01-Feb-2020	20-Mar-2020
Michigan	10-Mar-2020	18-Mar-2020
Minnesota	06-Mar-2020	21-Mar-2020
Mississippi	12-Mar-2020	19-Mar-2020
Missouri	06-Mar-2020	18-Mar-2020
Montana	11-Mar-2020	28-Mar-2020
Nebraska	06-Mar-2020	18-Mar-2020
Nevada	05-Mar-2020	27-Mar-2020
New Hampshire	03-Mar-2020	23-Mar-2020
New Jersey	04-Mar-2020	10-Mar-2020
New Mexico	11-Mar-2020	25-Mar-2020
New York	01-Mar-2020	14-Mar-2020
North Carolina	03-Mar-2020	25-Mar-2020
North Dakota	11-Mar-2020	27-Mar-2020
Ohio	09-Mar-2020	19-Mar-2020
Oklahoma	07-Mar-2020	19-Mar-2020
Oregon	28-Feb-2020	14-Mar-2020
Pennsylvania	06-Mar-2020	18-Mar-2020
Rhode Island	01-Mar-2020	28-Mar-2020
South Carolina	06-Mar-2020	16-Mar-2020
South Dakota	10-Mar-2020	18-Mar-2020
Tennessee	05-Mar-2020	20-Mar-2020
Texas	04-Mar-2020	17-Mar-2020
Utah	06-Mar-2020	22-Mar-2020
Vermont	19-Mar-2020	19-Mar-2020
Virginia	07-Mar-2020	14-Mar-2020
Washington	21-Jan-2020	29-Feb-2020
West Virginia	17-Mar-2020	29-Mar-2020
Wisconsin	05-Feb-2020	20-Mar-2020
Wyoming	11-Mar-2020	13-Apr-2020

Notes: We manually collected data on COVID-19 cases and deaths from each state's Department of Public Health (or equivalent) or other governmental sources. For states without publicly available data, we rely on local news reports.

Table A2: Index for Exposure to Disease

Occupation	Score	Occupation	Score
Top 15		*Bottom 15*	
Acute Care Nurses	100	Actuaries	0
Dental Hygienists	100	Aerospace Engineers	0
Family & Gen. Practitioners	100	Agents of Artists & Athletes	0
Internists, General	100	Art Directors	0
Critical Care Nurses	99	Assessors	0
Hospitalists	99	Auditors	0
Oral Surgeons	99	Automotive Engineers	0
Respiratory Therapists	98	Bicycle Repairers	0
Respiratory Therapy Technicians	98	Cabinetmakers Carpenters	0
Anesthesiologist Assistants	97	Camera & Photo Repairers	0
Occupational Therapy Aides	97	Cartographers and Photogrammetrists	0
Orderlies	97	City & Regional Planning Aides	0
Dental Assistants	96	Climate Change Analysts	0
Medical & Clinical Technologists	96	Commercial & Industrial Designers	0
Nurse Anesthetists	96	Computer Research Scientists	0

Notes: Our measure of exposure to disease is taken from a survey question asking "How often does this job require exposure to disease/infections?" with five possible answers: (1) Never, (2) Once a year or more but not every month, (3) Once a month or more but not every week, (4) Once a week or more but not every day, and (5) Every day. The translation of these responses into an index is done by O*NET.

Table A3: Index for Physical Proximity

Occupation	Score	Occupation	Score
Top 15		*Bottom 15*	
Choreographers	100	Fallers	7
Dental Hygienists	100	Fine Artists (e.g., Painters)	9
Physical Therapists	100	Poets and Creative Writers	14
Sports Medicine	100	Logging Equipment Operators	14
Dental Assistants	99	Hunters and Trappers	17
Dentists, General	99	Wellhead Pumpers	19
Oral Surgeons	99	Cooks, Private Household	21
Skincare Specialists	99	Farmworkers and Laborers	24
Surgical Technologists	99	Dredge Operators	27
Urologists	99	Bridge and Lock Tenders	28
Dancers	99	Pesticide Handlers & Applicators	29
Dermatologists	98	Environmental Economists	29
Prosthodontists	98	Petroleum Engineers	30
Radiation Therapists	98	Refuse & Recyclable Collectors	31
Respiratory Therapy	98	Political Scientists	31

Notes: This index is taken from a survey question asking "How physically close to other people are you when you perform your current job?" with five possible responses: (1) I don't work near other people(beyond 100 ft.), (2) I work with others but not closely(e.g., private office), (3) Slightly close (e.g., shared office), (4) Moderately close (at arm's length), and (5) Very close (near touching).

Table A4: COVID-19 and Unemployment: Demographic Characteristics

	(1)	(2)	(3)	(4)
Post COVID	0.0666	0.0572	0.0716	0.0550
	(0.0030)	(0.0032)	(0.003)	(0.003)
Male	0.0013	0.0009	0.0009	0.0009
	(0.0009)	(0.001)	(0.001)	(0.001)
Male × Post	-0.0101			
	(0.0026)			
16–34	0.0171	0.0165	0.0171	0.0171
	(0.00101)	(0.001)	(0.001)	(0.001)
35–54	-0.0002	-0.0001	-0.0002	-0.0002
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Hispanic	-0.0028	-0.0028	-0.0028	-0.0038
	(0.001)	(0.001)	(0.001)	(0.001)
Black	0.0101	0.0101	0.0101	0.0278
	(0.0028)	(0.0028)	(0.0028)	(0.0014)
Married	-0.0254	-0.0254	-0.0247	-0.0254
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
16–34 × Post		0.0149		
		(0.0034)		
35–54 × Post		-0.0031		
		(0.003)		
Married × Post			-0.0191	
			(0.003)	
Other non-white				0.0170
				(0.003)
Other × Post				0.0204
				(0.0098)
Black × Post				-0.0005
				(0.0056)
Hispanic × Post				0.0269
				(0.0047)
Asian × Post				0.0111
				(0.0056)
Observations	3070317	3070317	3070317	3070317
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is unemployed. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A5: COVID-19 and Labor Force Participation: Demographic Characteristics

	(1)	(2)	(3)	(4)
Post COVID	-0.0206	-0.0095	-0.0332	-0.0189
	(0.0031)	(0.0037)	(0.0033)	(0.0032)
Male	0.116	0.116	0.116	0.116
	(0.0057)	(0.0058)	(0.0058)	(0.0058)
Male × Post	-0.0043			
	(0.0029)			
16–34	0.191	0.192	0.191	0.191
	(0.0096)	(0.0097)	(0.0096)	(0.0096)
35–54	0.256	0.256	0.256	0.256
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Hispanic	0.0493	0.0493	0.0493	0.0497
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Black	0.0074	0.0074	0.0074	-0.0050
	(0.0062)	(0.0062)	(0.0062)	(0.0048)
Married	0.0393	0.0393	0.0385	0.0393
	(0.0021)	(0.0021)	(0.0022)	(0.0021)
16–34 × Post		-0.0297		
		(0.005)		
35–54 × Post		-0.006		
		(0.0041)		
Married × Post			0.0209	
			(0.0049)	
Other non-white				-0.0128
				(0.0051)
Other × Post				-0.0034
				(0.0088)
Black × Post				-0.0138
				(0.0062)
Hispanic × Post				-0.0092
				(0.0050)
Asian × Post				-0.0017
				(0.0117)
Observations	4378703	4378703	4378703	4378703
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A6: COVID-19 and Hourly Wages: Demographic Characteristics

	(1)	(2)	(3)	(4)
Post COVID	0.473	-0.0900	0.444	0.331
	(0.171)	(0.197)	(0.160)	(0.162)
Male	2.700	2.696	2.696	2.696
	(0.0717)	(0.0729)	(0.0729)	(0.0729)
Male × Post	-0.162			
	(0.139)			
16–34	-3.424	-3.444	-3.423	-3.424
	(0.0743)	(0.0745)	(0.0743)	(0.0743)
35–54	0.162	0.147	0.163	0.163
	(0.0580)	(0.0589)	(0.0581)	(0.0581)
Hispanic	-1.323	-1.322	-1.323	-1.320
	(0.0909)	(0.0909)	(0.0909)	(0.0908)
Black	-1.137	-1.138	-1.137	-1.782
	(0.205)	(0.205)	(0.205)	(0.0794)
Married	1.954	1.954	1.957	1.954
	(0.0658)	(0.0659)	(0.0674)	(0.0657)
16–34 × Post		0.660		
		(0.194)		
35–54 × Post		0.510		
		(0.259)		
Married × Post			-0.117	
			(0.171)	
Other non-white				-0.636
				(0.159)
Other × Post				0.143
				(0.450)
Black × Post				0.481
				(0.264)
Hispanic × Post				-0.0608
				(0.172)
Asian × Post				-0.0438
				(0.436)
Observations	390852	390852	390852	390852
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A7: COVID-19 and Hours of Work: Demographic Characteristics

	(1)	(2)	(3)	(4)
Post COVID	-0.318	-0.558	-0.788	-0.779
	(0.0843)	(0.192)	(0.0925)	(0.110)
Male	4.511	4.480	4.480	4.480
	(0.119)	(0.120)	(0.120)	(0.120)
Male × Post	-0.871			
	(0.105)			
16–34	-1.187	-1.181	-1.187	-1.187
	(0.0647)	(0.0686)	(0.0647)	(0.0647)
35–54	1.714	1.729	1.715	1.715
	(0.0760)	(0.0804)	(0.0760)	(0.0761)
Hispanic	0.169	0.169	0.169	0.176
	(0.137)	(0.137)	(0.137)	(0.137)
Black	0.560	0.560	0.560	0.142
	(0.133)	(0.133)	(0.133)	(0.0732)
Married	1.262	1.262	1.262	1.262
	(0.0593)	(0.0593)	(0.0585)	(0.0593)
16–34 × Post		-0.158		
		(0.219)		
35–54 × Post		-0.392		
		(0.213)		
Married × Post			0.00537	
			(0.0999)	
Other non-white				-0.422
				(0.0990)
Other × Post				0.170
				(0.327)
Black × Post				0.0566
				(0.227)
Hispanic × Post				-0.199
				(0.117)
Asian × Post				0.238
				(0.329)
Observations	2793158	2793158	2793158	2793158
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A8: COVID-19 Cases and Exposure, Proximity and Remote Work: State-Level

	Unemployment			
	Exposure	Proximity	Remote	Essential
Cum. COVID-19 cases per 10,000 people	0.0021	0.0021	0.0023	0.0021
	(0.0006)	(0.0006)	(0.0007)	(0.0006)
Index	-0.0034	0.0012	-0.0041	-0.0014
	(0.0003)	(0.0004)	(0.0003)	(0.0002)
Index × cases	0.0000	0.0007	-0.0010	-0.0001
	(0.0000)	(0.0002)	(0.0003)	(0.0001)
Observations	3058329	3058329	2866878	2945604
	Labor Force Participation			
	Exposure	Proximity	Remote	Essential
Cum. COVID-19 cases per 10,000 people	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Index	-0.0001	-0.0004	0.0003	0.0006
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index × cases	0.0000	-0.0001	0.0001	-0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Observations	3090005	3090005	2896179	2975856
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is a dummy for whether the individual is unemployed. In the bottom panel, the dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. $Cumulative\ Cases\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. In columns 1, 3 and 5, *Index* is our exposure to disease index, proximity to coworkers index and remote work index, respectively. In columns 2, 4 and 6, *Index Dummy* is a dummy for whether the individual is in an occupation above the median for our index of proximity to disease, proximity to coworkers and remote work, respectively. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A9: COVID-19 Cases and Exposure, Proximity and Remote Work: State-Level

	Wages			
	Exposure	Proximity	Remote	Essential
Cum. COVID-19 cases per 10,000 people	0.0130	0.0108	0.0124	0.0115
	(0.0069)	(0.0070)	(0.0066)	(0.0070)
Index	0.643	-0.0595	0.626	0.716
	(0.0363)	(0.0373)	(0.0693)	(0.0185)
Index × cases	-0.0089	0.0004	0.0079	-0.0007
	(0.0058)	(0.0052)	(0.0088)	(0.0027)
Observations	364752	364752	343578	350383
	Hours			
	Exposure	Proximity	Remote	Essential
Cum. COVID-19 cases per 10,000 people	-0.0141	-0.0147	-0.0173	-0.0140
	(0.0073)	(0.0077)	(0.0077)	(0.0074)
Index	-0.388	-0.693	0.512	0.327
	(0.0298)	(0.0524)	(0.0328)	(0.0165)
Index × cases	0.0021	0.0012	0.007	-0.0098
	(0.0019)	(0.0020)	(0.0018)	(0.0023)
Observations	2793158	2793158	2619263	2690316
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. In the bottom panel, the dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. $Cumulative\ Cases\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. In columns 1, 3 and 5, $Index$ is our exposure to disease index, proximity to coworkers index and remote work index, respectively. In columns 2, 4 and 6, $Index\ Dummy$ is a dummy for whether the individual is in an occupation above the median for our index of proximity to disease, proximity to coworkers and remote work, respectively. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A10: COVID-19 Deaths and Exposure, Proximity and Remote Work: State-Level

	Unemployment			
	Exposure	Proximity	Remote	Essential
Cumulative COVID-19 deaths per 10,000 people	0.0415	0.0413	0.0449	0.0413
	(0.0131)	(0.0133)	(0.0142)	(0.0131)
Index	-0.0034	0.0017	-0.0045	-0.0016
	(0.0003)	(0.0004)	(0.0003)	(0.0002)
Index × deaths	0.0001	0.0131	-0.0203	-0.0013
	(0.0005)	(0.0046)	(0.0067)	(0.0009)
Observations	3058329	3058329	2866878	2945604
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

	Labor Force Participation			
	Exposure	Proximity	Remote	Essential
Cumulative COVID-19 deaths per 10,000 people	-0.0056	-0.0055	-0.0059	-0.0057
	(0.0007)	(0.0007)	(0.0009)	(0.0007)
Index	-0.0001	-0.0007	0.0005	0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index × deaths	0.001	-0.0006	0.0008	-0.0005
	(0.0003)	(0.0013)	(0.0011)	(0.0007)
Observations	3090005	3090005	2896179	2975856
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is a dummy for whether the individual is unemployed. In the bottom panel, the dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. $Cumulative\ deaths\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 deaths per 10,000 inhabitants in the state. *Index* is our exposure to disease index, proximity to coworkers index, essential worker and remote work index, respectively. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A11: COVID-19 Deaths and Exposure, Proximity and Remote Work: State-Level

	Wages			
	(1) Exposure	(2) Proximity	(3) Remote	(4) Essential
Cumulative COVID-19 deaths per 10,000 people	0.256	0.201	0.254	0.228
	(0.160)	(0.161)	(0.160)	(0.166)
Index	0.641	-0.234	0.679	0.799
	(0.0340)	(0.0341)	(0.0695)	(0.0168)
Index × deaths	-0.224	-0.0227	0.272	-0.0756
	(0.104)	(0.0957)	(0.169)	(0.0634)
Observations	364752	364752	343578	350383
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

	Hours			
	(1) Exposure	(2) Proximity	(3) Remote	(4) Essential
Cumulative COVID-19 deaths per 10,000 people	-0.253	-0.261	-0.315	-0.249
	(0.132)	(0.140)	(0.141)	(0.134)
Index	-0.411	-0.851	0.625	0.420
	(0.0323)	(0.0504)	(0.0324)	(0.0201)
Index × deaths	0.0745	0.0862	0.139	-0.247
	(0.0370)	(0.0378)	(0.0322)	(0.0322)
Observations	2793158	2793158	2619263	2690316
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, the dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. In the bottom panel, the dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. *Cumulative deaths per*$10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 deaths per 10,000 inhabitants in the state. *Index* is our exposure to disease index, proximity to coworkers index, essential worker, and remote work index, respectively. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A12: COVID-19 Cases and Unemployment: Demographic Characteristics

	(1)	(2)	(3)	(4)
Cum. COVID-19 cases per 10,000 people	0.00216	0.00202	0.00230	0.00198
	(0.000762)	(0.000526)	(0.000787)	(0.000586)
Male	0.000974	0.000933	0.000933	0.000932
	(0.000963)	(0.000979)	(0.000978)	(0.000978)
Male × Case rate	-0.000143			
	(0.000314)			
16–34	0.0171	0.0170	0.0171	0.0171
	(0.00101)	(0.00101)	(0.00101)	(0.00101)
35–54	-0.000232	-0.000179	-0.000231	-0.000232
	(0.000735)	(0.000743)	(0.000735)	(0.000738)
Hispanic	-0.00280	-0.00280	-0.00281	-0.00318
	(0.00105)	(0.00105)	(0.00105)	(0.00107)
Black	0.0100	0.0100	0.0100	0.0281
	(0.00280)	(0.00280)	(0.00280)	(0.00141)
Married	-0.0254	-0.0254	-0.0253	-0.0254
	(0.000599)	(0.000599)	(0.000584)	(0.000599)
16–34 × Case rate		0.000398		
		(0.000288)		
35–54 × Case rate		-0.000187		
		(0.000145)		
Married × Case rate			-0.000426	
			(0.000341)	
Other non-white				0.0174
				(0.00271)
Other × Case rate				0.00201
				(0.00173)
Black × Case rate				-0.000758
				(0.000196)
Hispanic × Case rate				0.00128
				(0.000509)
Asian × Case rate				-0.000302
				(0.000319)
Observations	3070317	3070317	3070317	3070317
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is unemployed. *Cumulative Cases per*10,000 is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–March 2020.

Table A13: COVID-19 Cases and Labor Force Participation: Demographic Characteristics

	(1)	(2)	(3)	(4)
Cum. COVID-19 cases per 10,000 people	-0.0007	0.0000	-0.0011	-0.0005
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Male	0.116	0.116	0.116	0.116
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Male × Case rate	-0.0002			
	(0.0002)			
16–34	0.191	0.192	0.191	0.191
	(0.0096)	(0.0096)	(0.0096)	(0.0096)
35–54	0.256	0.256	0.256	0.256
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Hispanic	0.0493	0.0493	0.0493	0.0495
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Black	0.0074	0.0074	0.0074	-0.0053
	(0.0062)	(0.0062)	(0.0062)	(0.0047)
Married	0.0393	0.0393	0.0391	0.0393
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
16–34 × Case rate		-0.00134		
		(0.0005)		
35–54 × Case rate		-0.0007		
		(0.0003)		
Married × Case rate			0.0007	
			(0.0003)	
Other non-white				-0.0128
				(0.0051)
Other × Case rate				-0.0008
				(0.0004)
Black × Case rate				-0.0006
				(0.000186)
Hispanic × Case rate				-0.0005
				(0.0002)
Asian × Case rate				0.0000
				(0.0003)
Observations	4378703	4378703	4378703	4378703
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. $Cumulative\ Cases\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A14: COVID-19 Cases and Hourly Wages: Demographic Characteristics

	(1)	(2)	(3)	(4)
Cum. COVID-19 cases per 10,000 people	0.0154	-0.0130	0.0190	0.0128
	(0.00741)	(0.0167)	(0.00637)	(0.00911)
Male	2.696	2.695	2.695	2.695
	(0.0730)	(0.0729)	(0.0729)	(0.0729)
Male × Case rate	-0.00606			
	(0.00487)			
16–34	-3.424	-3.431	-3.424	-3.423
	(0.0743)	(0.0760)	(0.0743)	(0.0743)
35–54	0.163	0.157	0.163	0.163
	(0.0579)	(0.0579)	(0.0579)	(0.0580)
Hispanic	-1.323	-1.323	-1.323	-1.322
	(0.0909)	(0.0909)	(0.0909)	(0.0904)
Black	-1.137	-1.138	-1.138	-1.769
	(0.205)	(0.205)	(0.205)	(0.0795)
Married	1.954	1.954	1.957	1.954
	(0.0658)	(0.0659)	(0.0651)	(0.0658)
16–34 × Case rate		0.0354		
		(0.0160)		
35–54 × Case rate		0.0276		
		(0.0117)		
Married × Case rate			-0.0177	
			(0.0107)	
Other non-white				-0.639
				(0.163)
Other × Case rate				0.0633
				(0.0490)
Black × Case rate				0.00343
				(0.00578)
Hispanic × Case rate				-0.00338
				(0.0116)
Asian × Case rate				-0.0366
				(0.0101)
Observations	390852	390852	390852	390852
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. $Cumulative\ Cases\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A15: COVID-19 Cases and Hours of Work: Demographic Characteristics

	(1)	(2)	(3)	(4)
Cum. COVID-19 cases per 10,000 people	0.00435	-0.00519	-0.00739	-0.0138
	(0.00427)	(0.00661)	(0.00695)	(0.00916)
Male	4.488	4.480	4.480	4.480
	(0.121)	(0.120)	(0.120)	(0.120)
Male × Case rate	-0.0352			
	(0.00888)			
16–34	-1.186	-1.187	-1.186	-1.186
	(0.0647)	(0.0652)	(0.0647)	(0.0647)
35–54	1.715	1.720	1.715	1.714
	(0.0761)	(0.0768)	(0.0761)	(0.0761)
Hispanic	0.169	0.169	0.169	0.170
	(0.137)	(0.137)	(0.137)	(0.137)
Black	0.560	0.560	0.560	0.146
	(0.133)	(0.133)	(0.133)	(0.0720)
Married	1.262	1.262	1.265	1.262
	(0.0593)	(0.0593)	(0.0589)	(0.0593)
16–34 × Case rate		0.00476		
		(0.00439)		
35–54 × Case rate		-0.0233		
		(0.00424)		
Married × Case rate			-0.0119	
			(0.00303)	
Other non-white				-0.415
				(0.0964)
Other × Case rate				-0.0106
				(0.0130)
Black × Case rate				-0.00706
				(0.0101)
Hispanic × Case rate				-0.00760
				(0.00365)
Asian × Case rate				0.0248
				(0.00665)
Observations	2793158	2793158	2793158	2793158
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. $Cumulative\ Cases\ per 10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A16: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Unemployment

	(1)	(2)	(3)	(4)	(5)	(6)
State order	0.032	0.028	0.061	0.040	0.029	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
16–34	0.016	0.017	0.017	0.017	0.017	0.017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State order × 16–34	0.031					
	(0.006)					
35–54	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State order × 35–54	-0.008					
	(0.006)					
Female	-0.003	-0.004	-0.003	-0.003	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female with Children	0.005	0.005	0.005	0.005	0.005	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asian	0.001	0.001	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other non-white	0.018	0.018	0.018	0.018	0.017	0.018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Hispanic	-0.003	-0.003	-0.003	-0.003	-0.004	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black	0.028	0.028	0.028	0.028	0.028	0.028
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HS or less	0.058	0.058	0.058	0.058	0.058	0.057
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
HS, some college	0.019	0.019	0.019	0.019	0.019	0.018
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.026	-0.026	-0.025	-0.026	-0.026	-0.026
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State order × Female		0.024				
		(0.005)				
State order × Married			-0.040			
			(0.005)			
State order × Female with children				-0.003		
				(0.004)		
State order × Asian					0.013	
					(0.011)	
State order × Black					-0.002	
					(0.010)	
State order×Hispanic					0.042	
					(0.010)	
State order × Other					0.040	
					(0.016)	
State order × HS, some college						0.071
						(0.008)
State order × HS or less						0.086
						(0.011)
Observations	3070317	3070317	3070317	3070317	3070317	3070317
Test Rate	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is unemployed. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with demographic characteristics to examine heterogeneous impacts of stay-at-home orders. All columns control for the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A17: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Labor Force Participation

	(1)	(2)	(3)	(4)	(5)	(6)
State order=1	0.001	-0.022	-0.037	-0.021	-0.016	-0.003
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
16–34	0.192	0.191	0.191	0.191	0.191	0.191
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
State order × 16–34	-0.047					
	(0.006)					
35–54	0.257	0.257	0.257	0.257	0.257	0.257
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
State order × 35–54	-0.011					
	(0.005)					
Female	-0.115	-0.115	-0.115	-0.115	-0.115	-0.115
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Female with Children	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Asian	-0.052	-0.052	-0.052	-0.052	-0.052	-0.052
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Other non-white	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Hispanic	0.050	0.050	0.050	0.050	0.050	0.050
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Black	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HS or less	-0.359	-0.359	-0.359	-0.359	-0.359	-0.358
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
HS, some college	-0.116	-0.116	-0.116	-0.116	-0.116	-0.115
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Married	0.040	0.040	0.039	0.040	0.040	0.040
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State order × Female		0.003				
		(0.003)				
State order × Married			0.031			
			(0.005)			
State order × Female with children				0.002		
				(0.004)		
State order × Asian					0.001	
					(0.011)	
State order × Black					-0.018	
					(0.008)	
State order=1×Hispanic=1					-0.012	
					(0.005)	
State order × Other					0.003	
					(0.011)	
State order × HS, some college						-0.029
						(0.005)
State order × HS or less						-0.039
						(0.009)
Observations	4378703	4378703	4378703	4378703	4378703	4378703
Test Rate	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with demographic characteristics to examine heterogeneous impacts of stay-at-home orders. All columns control for the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A18: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Wages

	(1)	(2)	(3)	(4)	(5)	(6)
State order	0.121	0.783	0.835	0.713	0.683	0.662
	(0.541)	(0.471)	(0.471)	(0.457)	(0.473)	(0.511)
16–34	-3.432	-3.421	-3.421	-3.421	-3.421	-3.421
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
State order × 16–34	0.829					
	(0.371)					
35–54	0.159	0.168	0.168	0.168	0.168	0.168
	(0.058)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
State order × 35–54	0.684					
	(0.390)					
Female with Children	-0.017	-0.017	-0.017	-0.018	-0.017	-0.017
	(0.046)	(0.046)	(0.046)	(0.047)	(0.046)	(0.046)
Female	-2.688	-2.686	-2.687	-2.687	-2.687	-2.687
	(0.079)	(0.080)	(0.079)	(0.079)	(0.079)	(0.079)
Asian	-0.639	-0.639	-0.639	-0.639	-0.630	-0.639
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
Other non-white	-0.631	-0.632	-0.632	-0.632	-0.636	-0.632
	(0.161)	(0.161)	(0.161)	(0.161)	(0.163)	(0.161)
Hispanic	-1.323	-1.323	-1.323	-1.323	-1.324	-1.323
	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
Black	-1.768	-1.767	-1.767	-1.767	-1.771	-1.767
	(0.079)	(0.080)	(0.080)	(0.080)	(0.079)	(0.080)
HS or less	-8.051	-8.052	-8.052	-8.052	-8.052	-8.051
	(0.217)	(0.217)	(0.217)	(0.217)	(0.217)	(0.219)
HS, some college	-4.734	-4.734	-4.734	-4.734	-4.734	-4.736
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.095)
Married	1.955	1.955	1.958	1.955	1.955	1.955
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
State order × Female		-0.099				
		(0.295)				
State order × Married			-0.220			
			(0.329)			
State order × Female with children				0.098		
				(0.288)		
State order × Asian					-0.858	
					(0.399)	
State order × Black					0.286	
					(0.401)	
State order×Hispanic					0.125	
					(0.217)	
State order × Other					0.385	
					(0.660)	
State order × HS, some college						0.161
						(0.288)
State order × HS or less						-0.100
						(0.388)
Observations	390852	390852	390852	390852	390852	390852
Test Rate	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with demographic characteristics to examine heterogeneous impacts of stay-at-home orders. All columns control for the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A19: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Hours Worked

	(1)	(2)	(3)	(4)	(5)	(6)
State order	-0.161	-0.919	-0.336	-0.444	-0.442	-0.319
	(0.315)	(0.291)	(0.288)	(0.282)	(0.289)	(0.293)
16–34	-1.160	-1.160	-1.160	-1.160	-1.160	-1.160
	(0.068)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
State order × 16–34	0.044					
	(0.218)					
35–54	1.818	1.809	1.809	1.809	1.809	1.809
	(0.083)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
State order × 35–54	-0.607					
	(0.231)					
Female with Children	-0.559	-0.560	-0.559	-0.561	-0.560	-0.560
	(0.098)	(0.097)	(0.097)	(0.098)	(0.097)	(0.098)
Female	-4.220	-4.236	-4.220	-4.220	-4.220	-4.220
	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)
Asian	-0.596	-0.597	-0.597	-0.597	-0.603	-0.597
	(0.174)	(0.174)	(0.174)	(0.174)	(0.176)	(0.174)
Other non-white	-0.406	-0.405	-0.405	-0.405	-0.417	-0.406
	(0.096)	(0.095)	(0.096)	(0.096)	(0.098)	(0.096)
Hispanic	0.198	0.199	0.199	0.199	0.201	0.199
	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
Black	0.171	0.171	0.171	0.171	0.171	0.171
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
HS or less	-5.933	-5.933	-5.933	-5.933	-5.933	-5.932
	(0.413)	(0.413)	(0.413)	(0.413)	(0.413)	(0.416)
HS, some college	-1.989	-1.989	-1.989	-1.989	-1.989	-1.985
	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Married	1.330	1.330	1.332	1.330	1.330	1.330
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
State order × Female		1.092				
		(0.164)				
State order × Married			-0.149			
			(0.131)			
State order × Female with children				0.112		
				(0.235)		
State order × Asian					0.436	
					(0.389)	
State order × Black					-0.047	
					(0.293)	
State order×Hispanic					-0.157	
					(0.172)	
State order × Other					0.789	
					(0.417)	
State order × HS, some college						-0.260
						(0.126)
State order × HS or less						-0.051
						(0.385)
Observations	2793158	2793158	2793158	2793158	2793158	2793158
Test Rate	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with demographic characteristics to examine heterogeneous impacts of stay-at-home orders. All columns control for the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A20: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Unemployment (Indexes)

	(1)	(2)	(3)	(4)
State order	0.040	0.041	0.044	0.041
	(0.008)	(0.008)	(0.007)	(0.008)
Exposure to infection/disease index	-0.004			
	(0.000)			
State order×Exposure to infection/disease index	0.001			
	(0.002)			
Female	-0.003	-0.005	-0.004	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
Female with Children	0.008	0.007	0.007	0.007
	(0.001)	(0.001)	(0.001)	(0.001)
16–34	0.009	0.009	0.009	0.009
	(0.001)	(0.001)	(0.001)	(0.001)
35–54	-0.002	-0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Asian	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Other non-white	0.016	0.016	0.015	0.015
	(0.003)	(0.003)	(0.003)	(0.003)
Hispanic	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Black	0.025	0.024	0.024	0.024
	(0.001)	(0.001)	(0.001)	(0.001)
HS or less	0.041	0.041	0.038	0.042
	(0.003)	(0.003)	(0.003)	(0.003)
HS, some college	0.017	0.017	0.015	0.017
	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.023	-0.023	-0.023	-0.023
	(0.001)	(0.001)	(0.001)	(0.001)
Physical proximity to coworkers index		0.001		
		(0.000)		
State order×Physical proximity to coworkers index		0.035		
		(0.002)		
Remote work index			-0.004	
			(0.000)	
State order×Remote work index			-0.037	
			(0.003)	
Essential worker index				-0.001
				(0.000)
State order×Essential worker index				-0.008
				(0.002)
Observations	3058329	3058329	2866878	2945604
Test Rate	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is unemployed. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with our indexes to examine heterogeneous impacts of stay-at-home orders. All columns control for our full suite of demographic characteristics, the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A21: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Labor Force Participation (Indexes)

	(1)	(2)	(3)	(4)
State order	-0.007	-0.007	-0.007	-0.007
	(0.002)	(0.002)	(0.002)	(0.002)
Exposure to infection/disease index	-0.000			
	(0.000)			
State order×Exposure to infection/disease index	0.000			
	(0.001)			
Female	-0.004	-0.004	-0.004	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)
Female with Children	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
16–34	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)
35–54	0.008	0.008	0.008	0.008
	(0.000)	(0.000)	(0.000)	(0.000)
Asian	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Other non-white	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	0.003	0.003	0.003	0.003
	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HS or less	-0.013	-0.013	-0.013	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)
HS, some college	-0.004	-0.004	-0.004	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.003	0.003	0.003	0.003
	(0.000)	(0.000)	(0.000)	(0.000)
Physical proximity to coworkers index		-0.001		
		(0.000)		
State order×Physical proximity to coworkers index		-0.003		
		(0.001)		
Remote work index			0.000	
			(0.000)	
State order×Remote work index			0.003	
			(0.001)	
Essential worker index				0.001
				(0.000)
State order×Essential worker index				-0.000
				(0.001)
Observations	3090005	3090005	2896179	2975856
Test Rate	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy for whether the individual is in the labor force; were at work; held a job but were temporarily absent from work due to factors like vacation or illness; were seeking work; or were temporarily laid off from a job during the reference period. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with our indexes to examine heterogeneous impacts of stay-at-home orders. All columns control for our full suite of demographic characteristics, the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A22: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Wages (Indexes)

	(1)	(2)	(3)	(4)
State order	0.722	0.696	0.535	0.662
	(0.450)	(0.452)	(0.452)	(0.403)
Exposure to infection/disease index	0.648			
	(0.038)			
State order×Exposure to infection/disease index	-0.004			
	(0.132)			
Female with Children	-0.113	-0.011	0.003	-0.051
	(0.046)	(0.046)	(0.045)	(0.045)
Female	-3.028	-2.660	-2.923	-2.566
	(0.091)	(0.083)	(0.073)	(0.080)
16–34	-3.428	-3.395	-3.484	-3.490
	(0.074)	(0.074)	(0.072)	(0.075)
35–54	0.173	0.176	0.110	0.086
	(0.059)	(0.058)	(0.058)	(0.061)
Asian	-0.658	-0.628	-0.744	-0.772
	(0.130)	(0.133)	(0.147)	(0.145)
Other non-white	-0.635	-0.630	-0.593	-0.629
	(0.163)	(0.162)	(0.177)	(0.164)
Hispanic	-1.300	-1.327	-1.221	-1.317
	(0.095)	(0.091)	(0.079)	(0.087)
Black	-1.856	-1.762	-1.677	-1.710
	(0.082)	(0.079)	(0.073)	(0.080)
HS or less	-7.802	-8.050	-7.666	-7.993
	(0.221)	(0.218)	(0.198)	(0.225)
HS, some college	-4.531	-4.737	-4.534	-4.708
	(0.101)	(0.093)	(0.080)	(0.089)
Married	1.935	1.948	1.913	1.914
	(0.064)	(0.066)	(0.064)	(0.063)
Physical proximity to coworkers index		-0.124		
		(0.036)		
State order×Physical proximity to coworkers index		0.299		
		(0.097)		
Remote work index			0.658	
			(0.072)	
State order×Remote work index			-0.073	
			(0.206)	
Essential worker index				0.762
				(0.018)
State order×Essential worker index				-0.039
				(0.136)
Observations	390852	390852	368088	375368
Test Rate	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is the hourly wages for individuals currently employed as wage/salary workers, paid hourly, and were in outgoing rotation groups. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with our indexes to examine heterogeneous impacts of stay-at-home orders. All columns control for our full suite of demographic characteristics, the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A23: Heterogeneous Effects of Stay-at-Home Policies: Difference-in-Differences for Hours Worked (Indexes)

	(1)	(2)	(3)	(4)
State order	-0.429	-0.478	-0.461	-0.389
	(0.284)	(0.288)	(0.283)	(0.277)
Exposure to infection/disease index	-0.384			
	(0.032)			
State order×Exposure to infection/disease index	-0.094			
	(0.094)			
Female with Children	-0.508	-0.509	-0.547	-0.577
	(0.096)	(0.093)	(0.096)	(0.099)
Female	-4.034	-4.041	-4.395	-4.211
	(0.116)	(0.119)	(0.117)	(0.117)
16–34	-1.148	-1.017	-1.111	-1.177
	(0.066)	(0.063)	(0.072)	(0.072)
35–54	1.802	1.838	1.773	1.800
	(0.080)	(0.081)	(0.082)	(0.078)
Asian	-0.601	-0.592	-0.434	-0.575
	(0.171)	(0.175)	(0.200)	(0.191)
Other non-white	-0.394	-0.374	-0.320	-0.359
	(0.096)	(0.095)	(0.101)	(0.098)
Hispanic	0.210	0.229	0.265	0.165
	(0.137)	(0.137)	(0.144)	(0.138)
Black	0.247	0.255	0.241	0.193
	(0.075)	(0.072)	(0.078)	(0.078)
HS or less	-6.003	-5.747	-5.492	-5.958
	(0.414)	(0.419)	(0.441)	(0.418)
HS, some college	-2.041	-1.852	-1.707	-2.015
	(0.100)	(0.086)	(0.085)	(0.103)
Married	1.330	1.273	1.259	1.313
	(0.054)	(0.051)	(0.053)	(0.053)
Physical proximity to coworkers index		-0.784		
		(0.054)		
State order×Physical proximity to coworkers index		-0.115		
		(0.108)		
Remote work index			0.565	
			(0.035)	
State order×Remote work index			0.086	
			(0.096)	
Essential worker index				0.397
				(0.019)
State order×Essential worker index				-0.249
				(0.079)
Observations	2793158	2793158	2619263	2690316
Test Rate	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is hours of work for individuals who are employed and either at work or absent from work during the survey week, all jobs. *Stateorder* is a dummy indicating that a state has implemented a stay-at-home order. Columns add interactions of the treatment variable with our indexes to examine heterogeneous impacts of stay-at-home orders. All columns control for our full suite of demographic characteristics, the testing rate per 10,000 inhabitants and include state and month × year fixed effects.

Table A24: COVID-19 and Work Arrangement: National-Level

	(1)	(2)	(3)
Post COVID	0.0053	0.0053	0.0053
	(0.0009)	(0.0009)	(0.0009)
Cumulative COVID-19 cases per 10,000 people	0.0003	0.0003	0.0003
	(0.0001)	(0.0001)	(0.0001)
Observations	1799113	1799113	1799113
Indiv. Chars	No	Yes	Yes
State FE	Yes	Yes	Yes
Region × Year FE	No	No	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Interview Type FE	No	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy that equals one if an individual's usual work activities or duties have changed since last month. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. *Cumulative Cases per* $10,000$ is a variable equal to the number of cumulative number of confirmed COVID-19 cases per 10,000 inhabitants in the state. All columns include year, month and state fixed effects. Columns 2, 3, 5 and 6 add interview type fixed effects and the following demographic controls: gender, age, marital status and race. Columns 3 and 6 add education dummies and four Census region × year fixed effects. The time period is January 2016–April 2020.

Table A25: The Work Arrangement Impacts of COVID-19: Exposure, Proximity and Remote Work

	Exposure (1)	Proximity (2)	Remote (3)	Essential (4)
Post COVID	0.0058	0.0058	0.0056	0.0056
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Index	-0.0007	-0.0004	0.00002	0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Index × Post	0.0008	0.0005	0.0006	0.0005
	(0.0005)	(0.0004)	(0.0005)	(0.0007)
Observations	1799091	1799091	1686005	1733634
Indiv. Chars	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. The dependent variable is a dummy that equals one if an individual's usual work activities or duties have changed since last month. *Post COVID* is a dummy that is equal to one for the months of March and April 2020. In columns 1, 3 and 5, *Index* is our exposure to disease index, proximity to coworkers index and remote work index, respectively. In columns 2, 4 and 6, *Index Dummy* is a dummy for whether the individual is in an occupation above the median for our index of proximity to disease, proximity to coworkers and remote work, respectively. All columns include state, month, year, interview type and Census region × year fixed effects and the following demographic controls: gender, age, marital status, education and race. The time period is January 2016–April 2020.

Table A26: Effect of Stay-at-Home Policies: Synthetic Control Method Summary

	Mean	S.D.	Max	Min	Count
Cases per 10,000	-2.215	10.249	26.4	-15.6	20
Hours Worked	0.103	0.625	1.0	-1.5	20
Unemployment Rate	3.469	1.827	8.2	-0.5	20
Real Hourly Wage Rate	-0.213	0.991	2.2	-1.8	20
Labor Force Participation Rate	-0.008	0.016	0.0	-0.1	20

Notes: Data from the Current Population Survey. These are population weighted summary statistics of the estimated treatment effects for state-level synthetic controls. Treatment effects are defined as the treated state value less that of the synthetic control. States with greater than 0.66 weight placed on a single state in any of our outcomes of interest have been trimmed, the trimmed states are: Washington, Vermont, Rhode Island, New York, New Jersey, Montana, Minnesota, Louisiana, Colorado, and Alaska.