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Louis-Philippe Béland
Carleton University

Abel Brodeur
University of Ottawa and IZA

Taylor Wright
University of Ottawa

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Short-Term Economic Consequences of COVID-19: Exposure to Disease, Remote Work and Government Response*

In this ongoing project, we examine the short-term consequences of COVID-19 on employment and wages in the United States. Guided by a pre-analysis plan, we document the impact of COVID-19 at the national-level using a simple difference and test whether states with relatively more confirmed cases/deaths were more affected. Our findings suggest that COVID-19 increased the unemployment rate, decreased hours of work and labor force participation and had no significant impacts on wages. The negative impacts on labor market outcomes are larger for men, younger workers, Hispanics and less-educated workers. This suggest that COVID-19 increases labor market inequalities. We also investigate whether the economic consequences of this pandemic were larger for certain occupations. We built three indexes using ACS and O*NET data: workers relatively more exposed to disease, workers that work with proximity to coworkers and workers who can easily work remotely. Our estimates suggest that individuals in occupations working in proximity to others are more affected while occupations able to work remotely are less affected. We also find that occupations classified as more exposed to disease are less affected, possibly due to the large number of essential workers in these occupations.

JEL Classification: I15, I18, J21

Keywords: COVID-19, unemployment, wages, remote work, exposure to disease

Corresponding author:
Abel Brodeur
Social Sciences Building
University of Ottawa
120 University
Ottawa, ON K1N 6N5
Canada
E-mail: abrodeur@uottawa.ca

* This is an ongoing project. The most recent version of this paper is available here: https://sites.google.com/site/abelbrodeur/papers.

The COVID-19 pandemic has had vast tragic human consequences. As of the end of March 2020, there were over 800,000 confirmed cases and about 40,000 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 recession.[1]

In this paper, we explore the short-term economic consequences of COVID-19 on employment and wages in the United States. As of March 15, 2020 there were over 3,000 confirmed cases due to COVID-19 in the U.S. (Figure 1), with striking differences in the number of confirmed cases across states (Figures 2 and 3). The central questions in this paper are: (1) What are the short-term impacts of COVID-19 on employment and wages? (2) Are there larger effects for states with a greater number of COVID-19 cases and deaths? (3) Are there larger effects for relatively more 'risky' occupations? (4) Are there smaller effects for individuals in occupations who can easily work from home? To answer (3) and (4), we built indexes using data on exposure to disease, physical proximity to other people and how easily occupations can work from home using pre-COVID-19 data on method of transportation to work.

To answer these and a number of secondary questions we rely on the Current Population Survey (CPS). 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, unemployment, hours of work, occupation, industry and self-employment. The survey questions refer to activities during the week that includes the 12th of the month.

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)). As a novel approach to transparency in economics, we exploit the fact that the March 2020 CPS data was released only mid-April 2020, making it possible to pre-specified and publicly archived in a pre-analysis plan our analyses prior to obtaining the data.[2]

We first investigate the impact of COVID-19 at the national-level by documenting the evolution of the unemployment rate, labor force participation, hours of work and wages before and after the beginning of the pandemic. Taken as a whole, we find that COVID-19 led to an increase of about 1 percentage point in the unemployment rate, a decrease of about 0.7 percentage points in the labor force participation

[1]A preliminary UN's Trade and Development Agency downside scenario expects a \$2 trillion shortfall in global income with a \$US220 billion hit to developing countries (excluding China) (https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=2300).

[2]Our 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.

and a small decrease in hours of work. In contrast, hourly wages remained stable over the past two months. Importantly, many individuals were misclassified as "employed but not at work" instead of as "unemployed on layoff" for March 2020. This misclassification biases our estimates for unemployment effects downwards.[3] We thus 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. For unemployment, these explanations are approximately 15 percentage points more likely in March 2020. For reduced hours, the estimates suggest the explanations are 3 to 5 percentage points more likely.

We further document the impacts of COVID-19 by exploiting variation in state-level COVID-19 cases and deaths. For this analysis, we match individuals and the number of confirmed COVID-19 cases and deaths in their state of residence for the week that includes the 12th of the month, i.e., questions in the CPS refer to activities during the week prior to fieldwork. We find that the number of confirmed cases is positively correlated to state unemployment rate and negatively related to hours worked, suggesting that states with more COVID-19 cases were more affected by the pandemic in the short run.

We also investigate whether the short-term consequences of COVID-19 were larger for specific demographic groups. We find that the labor market effects were larger for men, younger workers, Hispanics and less-educated workers. These results suggest that COVID-19 may lead to an increase in the labor market inequalities. We also find that self-employed individuals are negatively affected by COVID-19.

We then investigate whether the economic consequences of this pandemic were larger for certain occupations. (See the Appendix 5 for the results for each major occupational category.) We built three different indexes using ACS and O*NET data: workers relatively more exposed to disease, workers that work with proximity to coworkers and workers who can easily work remotely. Our index of exposure to disease is defined as how often an occupation is exposed to infection or disease with responses ranging from "Never" to "Everyday". Our index of proximity to coworkers is defined as the extent to which an occupation performs tasks in close proximity to other people with answers ranging from "more than 100 feet away" to "Nearly touching". Our index of work remotely is defined as how frequently an occupation works from home based on ACS survey data. These indexes all range from 0 to 100, where 100 is the occupation with the most exposure to infection, closest proximity to others, or highest frequency of remote work.[4] Arguably, occupations who already

[3]This measurement error results in an approximately 0.9 percentage point increase in the unemployment rate over the officially reported figure. See section 4 for more details.

[4]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.

had a higher share of workers working remotely were less affected by COVID-19. Our estimates suggest that occupations that works in proximity to others are more affected while occupations able to work remotely are less affected. We also find that occupations classified as more exposed to disease are less affected, possibly due to the large number of essential workers in these occupations.[5] Having said that, by examining CPS data on explanations for current unemployment, we find that conditional on being unemployed these workers are more likely to have a COVID-19 related explanation.

In the subsection before the conclusion, we describe how we will document the economic consequences of policies which aims at reducing transmission of COVID-19 such as stay-home orders. Given that stay-home orders were implemented in late March and early April, 2020 we did not conduct this analysis yet.

We contribute to a growing literature on the economic consequences of COVID-19 (Alon et al. (2020); Atkeson (2020); Berger et al. (2020); Briscese et al. (2020); Fang et al. (2020); Fetzer et al. (2020); Jones et al. (2020); Jordá et al. (2020); Gollier and Straub (2020); Ramelli et al. (2020); Stephany et al. (2020); Stock (2020)).[6] One relevant study documenting the interaction between economic decisions and epidemics is Eichenbaum et al. (2020). They extend a canonical epidemiological model and argue that there is a trade-off between the severity of the short-term economic and health consequences of the epidemic. We contribute to this literature by focusing on the short-term labor market outcomes and documenting the heterogeneous impacts of COVID-19 by occupation.

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); Bell et al. (2006);Bloom et al. (2014); Correia et al. (2020); Goenka and Liu (2012); Lorentzen et al. (2008); Voigtländer and Voth (2013); Well (2007)). We complement these studies by documenting the short run impacts on labor markets of a new epidemic using disaggregated data on confirmed cases and deaths.

The rest of the paper is organized as follows. We first provide a brief history of the COVID-19 pandemic in the U.S. in section 1. In Section 2, we provide background on the plausible channels through which COVID-19 could affect employment and wages. Section 3 details the data collection and the identification strategy. We discuss the results in section 4. Section 5 concludes.

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

[6] Our paper also adds to a large literature investigating the relationship between heath and labor market outcomes (Currie and Madrian (1999); Strauss and Thomas (1998); Thirumurthy et al. (2008)).

1 Brief Timeline of COVID-19 in the United States

COVID-19 is a novel infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The disease was first identified in 2019 in Wuhan, China, and has since spread globally, resulting in a pandemic. The majority of cases result in mild symptoms with an estimated death rate of about 3.4 (World Health Organization (2020)).

Appendix Figure A1 provides a timeline of the pandemic for the U.S. The first case in the U.S. was a 35-year-old man who had returned from Wuhan, China to Washington State (Holshue et al. (2020)). The case was confirmed on January 20, 2020. The virus then hit six other states later in January and February: Arizona, California, Illinois, Massachusetts, Oregon and Wisconsin. These new confirmed cases were persons who had either returned from China or person-to-person transmission. The first case of community transmission, i.e., no known origin, was confirmed in California, on February 26, 2020. As of March 19, 2020, all 50 states had at least one confirmed case.

Appendix Table A1 shows the dates of the first confirmed case (column 1) and death (column 2) for each state.[7] Only Vermont and West Virginia had not announced a confirmed case by March 14, 2020, the last day March CPS respondents were interviewed.

2 Conceptual Framework

In this section, we provide a conceptual framework to better understand the channels through which COVID-19 may have affected employment and earnings. We discuss mechanisms tested in the empirical analysis, but also highlight other relevant economic channels.

2.1 Channels

The effect of COVID-19 on employment and wages is, *a priori*, ambiguous since many channels are at work.[8] A first channel through which COVID-19 may impact employment and wages is destruction of human capital. As of March 26, 2020 deaths from COVID-19 stood at 1,147 (Figure 1). It is thus unlikely that destruction of human capital had large (direct) short run impacts on employment and wages. But it is 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

[7] Appendix Figures A2 and A3 illustrate the number of states with at least one confirmed case and at least one death over time, respectively.

[8] See Goenka and Liu (2012) for a framework to study the economic impact of infectious diseases.

activity may be related to the health of other family members and friends (Berger and Fleisher (1984); Currie and Madrian (1999)).[9]

Increased uncertainty and fear may also have an impact on consumer behavior (Hassan et al. (2020)).[10] 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.

Uncertainty may also change investment behavior. Capital could tend to flow to states with relatively less COVID-19 cases. COVID-19 may also impact the allocation of productive capital across countries. For example, the exportation and production of N95 masks and other medical equipments (e.g., Whalen (2020)).

2.2 Impact on Specific Occupations and Industries

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 likelihood of contracting the disease.[11] We test in Section 4 whether COVID-19's economic impacts are related to how 'risky' an occupation is. On the one hand, there may be a wage premia 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.

Another important dimension is whether the worker is considered "essential." While the list of essential employees varies across locations, it usually includes health care and public health workers, law enforcement, first responders, food and agriculture workers, transportation, communications and information technology, critical manufacturing, financial services and security and U.S. military.[12] Essential

[9]Another channel through which COVID-19 could affect labor market outcomes is mental health problems (Ettner et al. (1997)).

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

[11]Using data on 25 locally transmitted cases in Singapore, Koh (2020) provides evidence that four cases were staff working in a store selling health products primarily to Chinese tourists and three cases were workers attending an international business meeting.

[12]The Department of Homeland Security (DHS) provides a useful list of essential critical infrastructure workers: `https://www.cisa.gov/identifying-critical-infrastructure-during-covid-19` Note that this list of the DHS is advisory, not a federal directive.

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 in Section 4 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 benefited from COVID-19 in the Appendix 5.

2.3 Government Response

Government interventions aimed at reducing transmission may have negative consequences on the economy (Eichenbaum et al. (2020)). Government response such as cancellations of trade shows, conventions and festivals, and mandated closure of "non-essential" industries, schools, daycare centers and other educational institutions will likely have a large negative impact on economic activity. Interestingly, the economic impacts could then be larger for industries categorized as "non-essential".

Note that the March 2020 CPS data refer to activities during the second week of the month, which means that no states had yet ordered its citizens to stay home (Appendix Table A2). We will thus be investigating the economic impacts of governors' "Stay Home" orders when revising this paper in May. Similarly, state governors started closing public and private schools by mid-March. According to the Department of Education's National Center for Education Statistics, school closures due to COVID-19 have impacted at least 124,000 public and private schools and affected more than 50 million students (Education Week (2020)).

3 Data and Identification Strategy

In this section, we describe our data sets. We also provide information on COVID-19 cases and fatalities, and how they vary over time and across states. Last, we detail our specification and controls, which were pre-specified in a pre-analysis plan.

3.1 COVID-19

Unfortunately, the CDC is not currently publishing disaggregated data at the day- or week-level for each state. For this project, we thus 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. We checked the accuracy of our data by comparing it to similar database created and maintained by other groups of researchers or institutions such as the COVID Tracking Project (https://covidtracking.com/).

Data at the national-level is reported and updated by the CDC on a regular basis.[13] Our figures at the state-level match their national estimates, suggesting that the extent of measurement error in the number of cases in our database is not important. But 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.

Figures 2 and 3 illustrate the geographical distribution of COVID-19 cases and deaths at the state-level as of March 15, 2020. The states of New York, Washington and California have the most confirmed cases with 729, 642 and 293, respectively. The average number of cases is 64 (std. dev. 138), with 13 states with less than 10 confirmed cases.

3.2 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, unemployment, hours of work, occupation and industry. The survey questions refer to activities during the week that includes the 12th of the month. We will also study the impact of COVID-19 on self-employed

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

workers. There are two groups of self-employed workers in the CPS: incorporated (those who work for themselves in corporate entities) and unincorporated (those who work for themselves in other entities). We will study the impact of COVID-19 on both.

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 2020, only telephone interviews were conducted and two call centers were closed. The response rate (73%) was therefore about 10 percentage points lower than in preceding months (U.S. Bureau of Labor Statistics (2020)). 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 variables of interest. Our sample consists of civilians aged 16–70 over the time period January 2016 to March 2020. We have 3,024,280 observations for unemployment. Our sample size is smaller for hourly wages since this information is only asked of the outgoing rotation groups. Approximately 4.3% 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.

3.3 Occupational Measures of Exposure and Remote Work

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 the Appendix Figure A4.[14] The top and bottom 15 occupations are shown in Appendix Table A3. The following four occupation codes have a score of 100: Acute 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 A5. The top and bottom 15 occupations are shown in Appendix Table A4. 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 creating an index capturing how easily occupations can work from home using data from the American Community Survey 2014–2018. We calculate the share of workers in each occupation who answered "Worked at home" as their response to a question asking about a respondent's method of transportation to work. We then divide this share of workers by the median occupation's share of home workers and multiply by 100.

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 the explorer and proximity 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. Table 1 provides descriptive statistics. For our three indexes, the maximum value is 100 and the minimum value is 0 (0.2 for physical proximity). Exposure to infection/disease, physical proximity to coworkers and remote work have a mean (standard deviation) of 22 (24), 61 (17) and 11 (13), respectively.

Figure 4 illustrates our three 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 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

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

to infection and disease. The color of the circles corresponds to the quartile of each occupation in the remote work index we constructed. Occupations in the first quartile are more commonly done from home while those in the fourth quartile are not commonly done from home.[15]

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 0.532. In contrast, there is a negative correlation between remote work and exposure (correlation of -0.161), 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 -0.066).

3.4 Identification Strategy

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 2020 and zero for all preceding months. The time period is January 2016 to March 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.

Only year, month and state fixed effects are included in the basic model. We enrich the basic model by controlling for demographic characteristics, the educational level of the respondent and interview type fixed effects, i.e., telephone or in-person.

[15] We also present variants of this in Appendix Figures A6 and A7 where we plot the remote work index on the x-axis and the other indexes as quartiles and along the y-axis.

Moreover, to allow for common regional shocks to a given economic outcome, we estimate specifications that include interactions between year fixed effects and the four Census regions. We report standard errors clustered at the state-level.

We then investigate the impact of COVID-19 at the state-level. In this analysis, we exploit variation in cases and fatalities over time across states. The model is:

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

where $y_{i,s,t}$ is an economic outcome for individual i in state s and month t. $CASES_{s,t}$ is the number of confirmed cases per 10,000 inhabitants in state s in time t. In some model, we replace the variable $CASES_{s,t}$ by $DEATHS_{s,t}$, which capture the number of COVID-19 fatalities per 10,000 inhabitants. (We rely on confirmed cases rather than fatalities in this version of the paper because of the very small number of COVID-19 deaths as of March 14, 2020.) Finally, θ_s and δ_t represent state and time fixed effects, respectively.

A potential concern for the identification is that some states were able to perform tests earlier than others or that they were more proactive at testing. We doubt it is an issue for three reasons. First, as of March 14, 2020 all states were able to perform tests, with a doctor's approval. Second, states' willingness to test for COVID-19 would need to be correlated to changes in the labor market in order to bias our estimates. Third, we argue that knowledge of confirmed cases is the main driver of fear and uncertainty rather than the total number of people infected, which is unknown. Note that we will also rely on deaths in future version of this work.

4 Short Run Economic Consequences

In this section, we describe the relationship between COVID-19 and wages and employment status using the CPS. 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. We also explore throughout the heterogeneous impacts of COVID-19, with a particular focus on our measures of exposure and remote work. Last, we discuss the plausible effects of government policies such as stay-home orders.

4.1 Employment and Wages: National-Level

We begin our analysis with a graphical representation of the effect of COVID-19 on our four main labor market outcomes. Figure 5 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 March 2020. Looking at these figures, we observe a visible increase in the unemployment rate in March 2020, suggesting large effects of COVID-19 on the U.S. labor market. More precisely, the unemployment rate increased by about 0.9 percentage point from February to March 2020, reaching 4.5 percent. The unemployment rate had not been this high since January 2018. Similarly, there was a decrease in labor force participation of about 0.6 percentage points. For hours of work, workers experienced a small drop of approximately 0.25 hours from February to March 2020. Last, hourly wages remained stable over the past two months, possibly due to compositional changes in the labor force.

We now investigate with graphical representations the short-term effects of COVID-19 on labor market outcomes for different subgroups of respondents. Appendix Figures A8, A9, A10, A11 and A12 illustrate our outcome variables by gender, age groups, marital status, race and education groups, respectively. The structure is the same as in Figure 5. For the analysis by gender presented in Appendix Figure A8, we find that both male and female are negatively affected by the pandemic. Our graphical evidence suggests that the decreased in hours of work and wages are more pronounced for men than women.[16] This will be studied further in Appendix Tables A5-A8.

We next document the impact of COVID-19 by age groups. COVID-19 may have heterogenous impacts on labor supply since a majority of COVID-19 deaths have occurred among adults aged over 60 years old and that younger individuals were the least affected (Centers for Disease Control and Prevention (2020)). Appendix Figure A9 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, especially for unemployment.

We next document the impact of COVID-19 by marital status. Appendix Figure A10 shows that both married and non-married's employment are negatively affected. Appendix Figure A11 splits the sample by race. It presents results for white, blacks, Hispanics and asian separately. This figure illustrates that all groups are negatively affected by COVID-19 but the decline in employment, wages and hours of work seem larger for non-white, especially Hispanics. 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)). 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 A12 we present results by educational attainment. We

[16]See Currie and Madrian (1999) for a brief literature review of gender differences in the effects of health on participation.

split individuals in three groups: (1) less than high school, (2) high school degree, and (3) associate-bachelor or graduate degree. Appendix Figure A12 shows that the negative impact of COVID-19 on employment is more pronounced on less educated workers.

Appendix Figure A13 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 1 percentage point and a decrease in both hours of work and hourly wages. In contrast, native born workers experienced an increase of about 0.5 percentage point in the unemployment rate and virtually no change in hours of work and hourly wages. This is potentially troublesome due to the well known labor market gap between native born and immigrant workers.

We now turn to our regression analysis, and Table 2 presents the baseline results. This table contains OLS estimates of equation (1) for our four outcome variables. The time period is January 2016 to March 2020. The dependent variables are respectively the unemployment rate (Panel (a), columns 1–3), labor force participation (Panel (a), columns 4–6), hours of work (Panel (b), columns 1–3) and hourly wages (Panel (b), columns 4–6). We report standard errors clustered by state.

What clearly emerges is that COVID-19 is associated with an increase in the unemployment rate, a decrease in labor force participation and a decrease in hours of work. In contrast, there is no significant changes in wages. In columns 1 and 4, we include only state, month and year fixed effects, and find that the unemployment rate increased by about 1 percentage point, labor force participation dropped by 0.7 percentage points and hours of work decreased by 0.45 in March 2020. The estimates are all statistically significant at the 1 percent level. The estimate for hourly wages is small, positive and statistically insignificant. 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)).

In columns 2 and 5, we add to our model demographic controls (age, gender, marital status and race) and interview type fixed effects. In columns 3 and 6, also control for the educational attainment of the respondent Census region and region $\times$ year fixed effects. Overall, the magnitude and statistical significance of the estimates remain the same.

For the CPS March 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 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".[17] 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 6. The top panel 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 15 percentage points more likely in March 2020. The middle panel 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 5 percentage points more likely in March. The bottom panel contains estimates for the explanations of work absences and the dependent variable is a dummy that equals one if the explanation for being absent is "other reasons".

[17] 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)).

This COVID-19 related explanation is about 19 percentage points more likely in March. 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. Table 6 is discussed below and attempts to provide insight into which types of workers and occupations are more affected by this underestimation of unemployment.

We now investigate heterogeneous effects of COVID-19 by gender, age, martial status and race. The dependent variables are the unemployment rate, labor force participation, hourly wages and hours of work in Appendix Tables A5, A6, A7 and A8, respectively. 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. Other race(s) being the omitted category.

We find that the labor market impacts of COVID-19 are significantly larger for men than for women. We also find that COVID-19 has larger effects on younger workers' (aged 16 to 34) labor force participation. Moreover, these tables find smaller negative effects for married individuals for labor force participation and that Hispanics are significantly more likely to be unemployed due to COVID-19.

4.1.1 Impacts by Occupation: National-Level We now explore whether COVID-19, as of March 2020, had larger impacts on workers relatively more exposed to disease, proximity to coworkers and who can easily work remotely.[18] As discussed above, our indexes are defined as follows. Our index of exposure to disease is defined as how often an occupation is exposed to infection or disease with responses ranging from "Never" to "Everyday". Our index of proximity to coworkers is defined as the extent to which an occupation performs tasks in close proximity to other people with answers ranging from "more than 100 feet away" to "Nearly touching". Our index of work remotely is defined as how frequently an occupation works from home based on ACS survey data. These indexes all range from 0 to 100, where 100 is the occupation with the most exposure to infection, closest proximity to others, or highest frequency of remote work.

Figure 6 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 decline in labor force participation than those workers in below median exposure occupations, but the magnitude is still less than 1 percentage point lower from the

[18] In Appendix Figures A17–A38 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.

participation rate in December 2019. Individuals in both groups seem to experience large unemployment responses. For workers in occupations with above median exposure, hourly wages seem to increase in February before declining in March while for below median workers there is a decline in both months. This could indicate that initially, low wage earners among the above median occupations found themselves unemployed while the higher wage earners began to be affected in March. Hours of work appear to be declining for both groups.

Figure 7 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 in unemployment around the onset of COVID-19 as well as a bump in average hourly wage. This perhaps suggests that it was low wage workers in the above median group that transitioned into unemployment. Labor force participation is nearly 100% for both groups, almost by definition.

Figure 8 shows the split for individuals in occupations above and below the median for our index of pre-COVID-19 remoteness of work. This figure illustrates that workers in occupations with a remote work index over the below the median experienced a much larger increase in the likelihood to be unemployed and decrease in hours of work. More precisely, individuals in occupations below the median saw an increase in the unemployment rate that is about 40% higher than individuals in occupation above the median.

Tables 4, 5, and 6 are structured identically and formally test whether COVID-19 had different impacts on these subgroups of workers. Specifically, Table 4 contains estimates for unemployment and labor force participation, Table 5 for hourly wages and hours of work and Table 6 handles COVID-19 related explanations for unemployment and reduced hours of work, respectively. All columns include our usual set of fixed effects and demographic controls. In columns 1, 3 and 5, we include $Post\ COVID$, $Index$ and the interaction of these two variables. $Index$ corresponds to one of our three indexes, and ranges from 0 to 100. In columns 2, 4 and 6, we replace $Index$ by $Index\ Dummy$, which is a dummy for whether the individual is in an occupation above the median for our indexes (proximity to coworkers, exposure to disease, remote work).

In columns 1 and 3, we confirm our previous result that workers relatively more exposed to disease are significantly less likely to be affected by COVID-19. The point estimates for both interaction terms ($Index \times PostCOVID$ and $Index\ Dummy \times PostCOVID$) for unemployment are negative but statistically only for $Index$ (at the 1% level). For hours of work and hourly wages our estimates are positive but statistically insignificant at conventional levels. We similarly find that those who are relatively more exposed to disease are less likely to report COVID-19 related reasons for reduced work hours (for both interaction terms). These differences are statistically significant at the 5% level. We do not find evidence of differential responses in COVID-19 related explanations for absences. In contrast, we find positive and statistically significant changes in COVID-19 related explanations of unemployment for both interactions terms. This suggests that while workers with more exposure are no more likely than those with less exposure to be unemployed, those who are unemployed are more likely to have a COVID-19 related explanation.

In columns 3 and 4, we provide the analysis for our proximity to coworkers index. We find that the interaction terms for both $Index$ and $Index\ Dummy$ with $Post\ COVID$ are positive for unemployment but only that of $Index\ Dummy$ is statistically significant at conventional levels. For hours of work, we find negative effects for both interaction terms, though only the $Index\ Dummy$ interaction is statistically significant at conventional levels. We find no evidence of differential responses between the groups for wages or labor force participation.

We also find that workers in closer proximity to their coworkers are more likely to indicate one of the COVID-19 related explanations for unemployment (for both the interaction terms). These results are statistically significant at the 1% level and imply that workers that are unemployed are more likely to be so for COVID-19 related reasons. For COVID-19 related explanations of work absences we find a positive and statistically significant effect (about 7 percentage points for the dummy version of the index) for both interaction terms, implying that the underestimation of unemployment may be particularly severe for these workers.

Columns 5 and 6 investigate the impact of COVID-19 on our remote work index. The interaction terms for $Post\ COVID$ and $Index$ and $Index\ Dummy$ are both negatives and statistically significant at conventional levels for the unemployment rate, suggesting that COVID-19 had larger impacts on occupations in which workers cannot easily work remotely. We also find similar evidence for hours of work with positive coefficients for both interaction terms, although only the interaction with $Index\ Dummy$ is statistically significant. In contrast, we find no evidence that the hourly wages and labor force participation of the two subgroups of workers were differently affected. Nor do we see different responses from the subgroups in COVID-19 related explanations for unemployment, work absences, or reduced hours.

Next, we distinguish between part-time and full-time workers. Appendix Figure A14 shows that COVID-19 led to negative labor market outcomes for both full-time and part-time workers. This figure suggests that a large fraction of full-time workers became unemployed in March while part-time workers saw a decrease in hours and hourly wages.

We also split the sample for unionized workers versus nonunionized workers in Appendix Figure A15. The pattern illustrated in this figure suggests that the labor effects of COVID-19 are smaller for union workers than non-union workers. Unionized workers might have more bargaining power to avoid layoff during the pandemic and may be more likely to be in essential industries, e.g., health and public services.

We also analyze the impacts of COVID-19 on self-employed workers in Appendix Figure A16. It separates between incorporated and unincorporated. As described in the data section, 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 A16 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.

4.2 Employment and Wages: State-Level

Figure 9 plots our labor market outcomes for individuals split by states with cumulative known COVID-19 case rates above and below the median. As with Figure 5, Panel (a) plots the unemployment rate, Panel (b) the labor force participation rate, Panel (c) hours of work, and Panel (d) hourly wages. States above and below the media case rate experienced very similar trends and levels of unemployment. Looking more specifically at the change from February 2020 to March 2020, both subgroups of states saw a jump in unemployment. States with above median case rates have roughly 1 percentage point higher labor force participation than below median states, though they experience very similar trends. The drop in labor force participation from February 2020 to March 2020 looks marginally larger for states above median than below at around -0.5 percentage points. The difference in hours worked per week between the two groups appears to be about a half an hour over our sample, with below median states working more. March 2020 saw a small uptick in hours worked for above median states while below median states saw a decline of nearly half an hour. Lastly, above median states tend to have higher hourly wages over our sample, roughly \$1, while experiencing very similar trends to below median states. Both groups saw a very slight decline in wages for March 2020 from February 2020, which itself saw an increase over January 2020 of about \$0.30 for above median states and roughly \$0.15 for below median states.

The results derived from estimating equation (2) are reported in Table 7. The dependent variable is the unemployment rate in columns 1–4, Panel (a), labor force participation in columns 5–8, Panel (a), the hourly wages in columns 1–4, Panel (b) and hours of work in columns 5–8, Panel (b), respectively. The variable of interest is the number of cumulative known COVID-19 cases per 10,000 inhabitants. In columns 4 and 8, we also include the number of cumulative known COVID-19 cases per 10,000 inhabitants squared.

We find that the number of cumulative number of cases at the state-level is positively correlated to the unemployment rate and negatively related to labor force participation and hours of work, suggesting that individuals in states with more COVID-19 cases were more affected. The estimates for wages are positive, but statistically insignificant. An increase of 1 known case per 10,000 inhabitants is associated with an increase in the unemployment rate of 2 percentage points. Recall that the confirmed number of cases is very small as of March 2020.

The squared term is meant to explore the possibility that the relationship between the cumulative case rate and unemployment (or any of our labor market outcomes) is concave, i.e., additional cases are associated with an increase in the likelihood of unemployment but as the state becomes saturated with cases the change in unemployment risk is less severe. In that situation, we would expect a negative coefficient on the squared term and a positive coefficient on the coefficient for cases. This could be as a result of layoffs slowing down after the initial wave stemming from government policies. This is in fact the relationship that our estimates suggest for the likelihood of unemployment. This direction of our results for hourly wages and hours of work are also consistent with a concave relationship but are not statistically significant. The estimates for labor force participation are consistent with a convex shape, that each case is associate with a lower probability of being in the labor force but that decline evens out with additional cases. This could be consistent with a kind of survivorship bias, those workers who remain in the labor force after the initial stages of of the pandemic are essential workers who will not leave.

4.2.1 Impacts by Occupation: State-Level Tables 8 and 9 provide estimates for the differential effects of COVID-19 on workers across our exposure, proximity, and remote work indexes.[19] These tables are the equation (2) analogs of Tables 4 and 5 and are structured the same way. The only difference is that

[19] As mentioned above, our index of exposure to disease is defined as how often an occupation is exposed to infection or disease with responses ranging from "Never" to "Everyday". Our index of proximity to coworkers is defined as the extent to which an occupation performs tasks in close proximity to other people with answers ranging from "more than 100 feet away" to "Nearly touching". Our index of work remotely is defined as how frequently an occupation works from home based on ACS survey data. These indexes all range from 0 to 100, where 100 is the occupation with the most exposure to infection, closest proximity to others, or highest frequency of remote work.

we replace *Post COVID* with the cumulative known COVID-19 cases per 10,000 inhabitants. Table 8 present results for outcomes unemployed and in labor force and Table 9 present results for outcomes wages and hours worked.

We find that occupations that are exposed to infection or disease are less likely to be unemployed due to COVID-19 while occupations that work in close proximity to others are more likely to be unemployed and work less hours. We also find that workers in occupations that can work remotely are less likely to be unemployed. The effects are significant at the 1% level. These results are in line with our national-level analysis.

4.3 Government Response

In this last subsection, we will explore the economic consequences of implementing policies to reduce transmission of COVID-19. The evidence has so far suggested that locking down (or stay-home orders) 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.[20] Appendix Table A2 lists stay-home orders and school closures as of March 27, 2020.

Stay-home orders are, arguably, the most relevant since they (partially) limit people's ability to work. Given that stay-home orders were implemented in late March and early April, 2020 we did not conduct this analysis yet. We will conduct it in a revised version. This subsection would thus explore whether states that implemented stay-home orders had worse labor market outcomes after the epidemic started, conditional on COVID-19 cases/deaths and governors' characteristics.[21] In other words, we would compare states with and without stay-home orders in a traditional difference-in-differences framework.

5 Conclusion

We study here the relationship between COVID-19 and U.S. employment and wages at the national- and state-level. Using data on COVID-19 cases, and data from the CPS, we find that COVID-19 increased the unemployment rate, decreased hours of work and labor force participation and had no significant impacts on wages. These results are important given the current tradeoff faced by state governors between employment and disease prevention (Baccini and Brodeur (2020); Eichenbaum et al. (2020); Oswald and Powdthavee (2020)).

[20] A growing number of studies also point out the impacts of lockdowns on health and well-being (e.g., Brodeur et al. (2020) and Hamermesh (2020)).

[21] Baccini and Brodeur (2020) provide evidence that Democratic governors and governors without a term limit are significantly more likely to implement stay-at-home orders and significantly faster to adopt.

Our analysis also documented heterogeneous effects of COVID-19 across occupations and workers. The findings suggest that COVID-19 affect disproportionally men, younger workers, Hispanics and less-educated workers. We also investigate whether the economic consequences of this pandemic were larger for certain occupations. We built three indexes using ACS and O*NET data: workers relatively more exposed to disease, workers that work with proximity to coworkers and workers who can easily work remotely. Our estimates suggest that occupations that work in proximity to others are more affected while occupations able to work remotely are less affected. We also find that occupations classified as more exposed to disease are less affected, possibly due to the large number of essential workers in these occupations. 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 (e.g., Fortson (2011)), early-life exposure (e.g., Bleakley (2010)) and labor market discrimination (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); Bell et al. (2006); Pamuk (2007)). Numerous studies point out that real wages rose after the Black Death (Goldberg (1992); Poos and Poos (2004)) 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)). One major difference between COVID-19 and AIDS is that COVID-19 is not transmitted sexually and should not lead to a reduction in fertility (Boucekkine et al. (2009)). The long-term economic consequences of COVID-19 thus remain unknown at this point. The human suffering brought about by the epidemic and its economic consequences are depressing in the short run.

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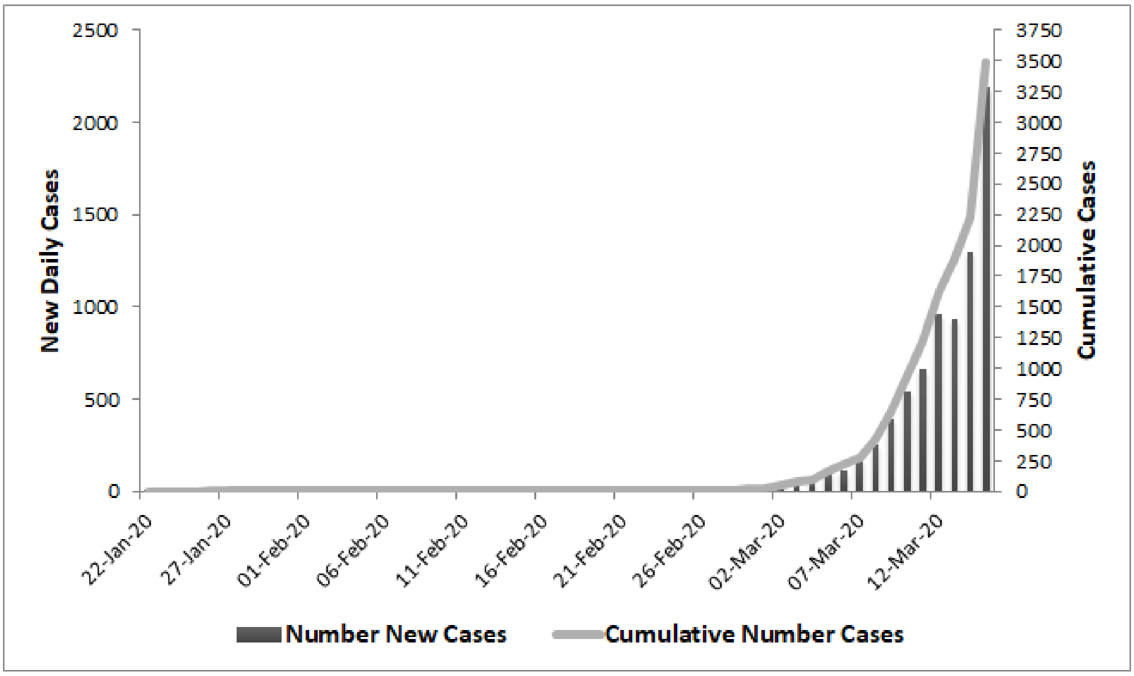
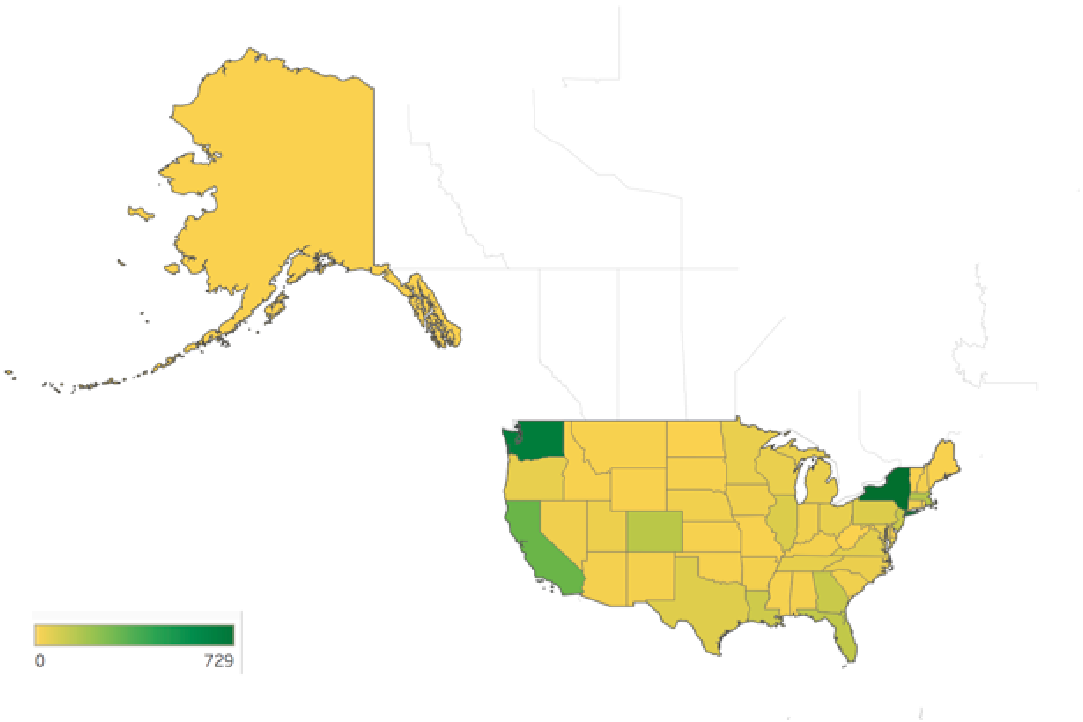
Figure 1: COVID-19 Confirmed Cases in the United States



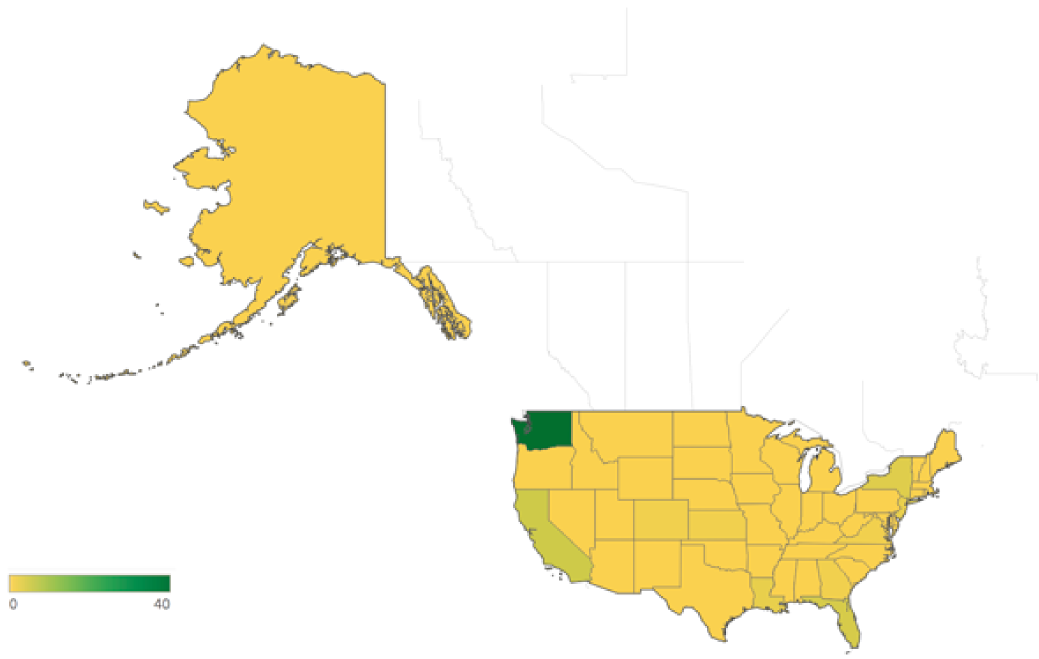
Notes: The primary vertical axis illustrates daily new (confirmed) COVID-19 cases in the United States. The second vertical axis shows the cumulative number of (confirmed) COVID-19 cases in the United States. The data does not include cases among persons repatriated to the U.S. from Wuhan, China and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

Figure 2: 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 3: COVID-19 Deaths by State

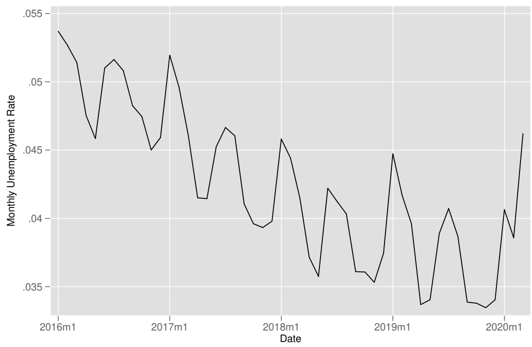


Notes: The map illustrates the number of COVID-19 deaths for each state as of March 15, 2020.

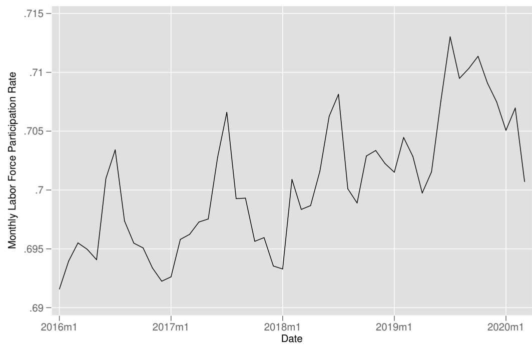
Figure 4: Physical Proximity, Exposure to the Disease and Remote Work by Occupation

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 quartile of each occupation in the remote work index we constructed. Occupations in the first quartile are more commonly done from home while those in the fourth quartile are not commonly done from home.

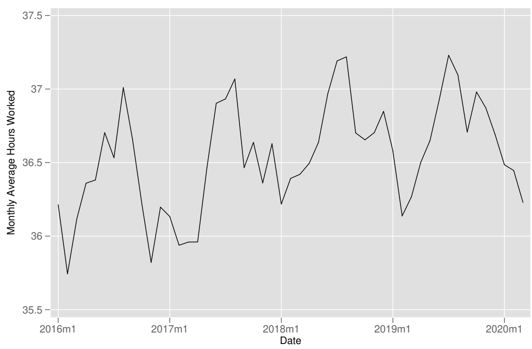
Figure 5: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages.



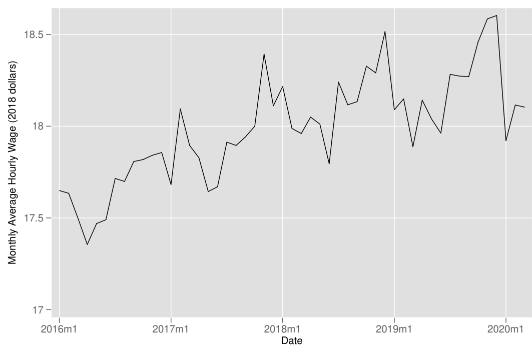
(a) Unemployment Rate.



(b) Labor Force Participation.



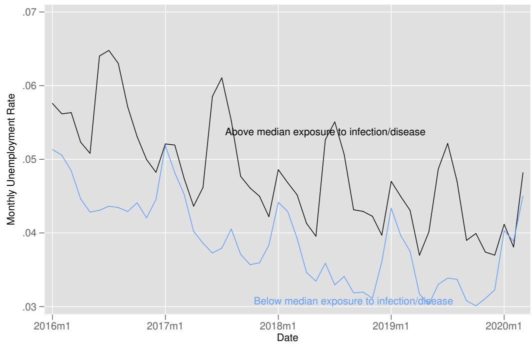
(c) Hours of Work.



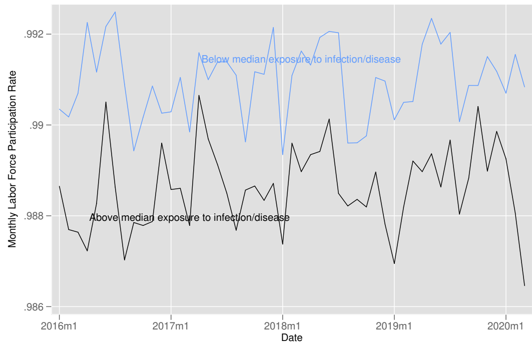
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

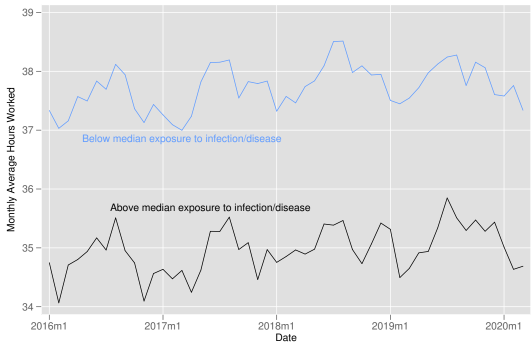
Figure 6: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Exposure to Disease.



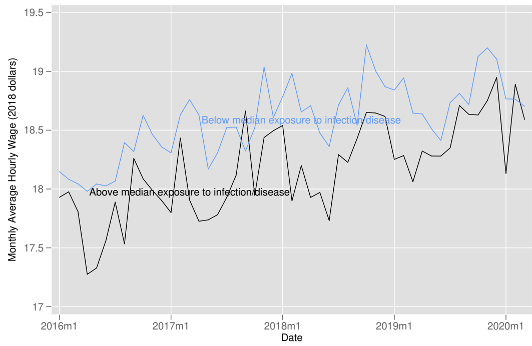
(a) Unemployment Rate.



(b) Labor Force Participation.



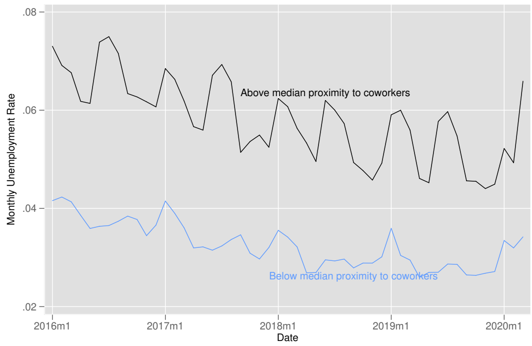
(c) Hours of Work.



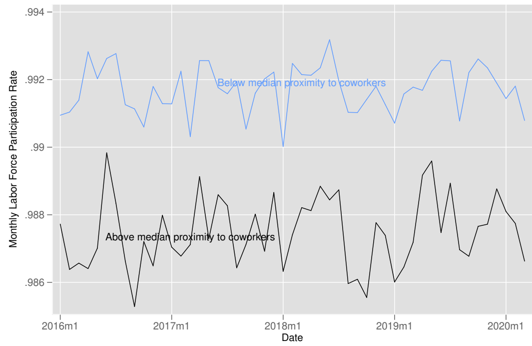
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

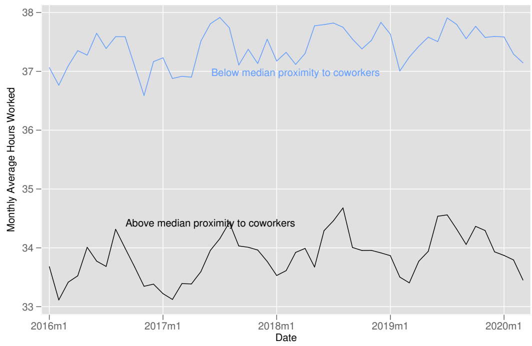
Figure 7: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Proximity to Coworkers.



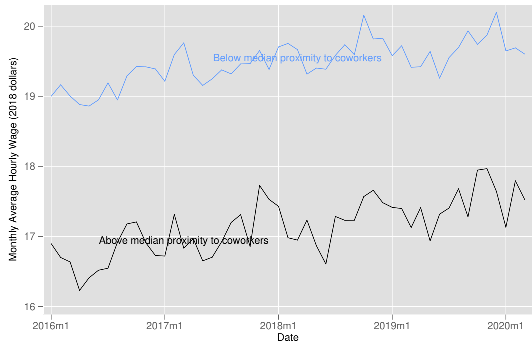
(a) Unemployment Rate.



(b) Labor Force Participation.



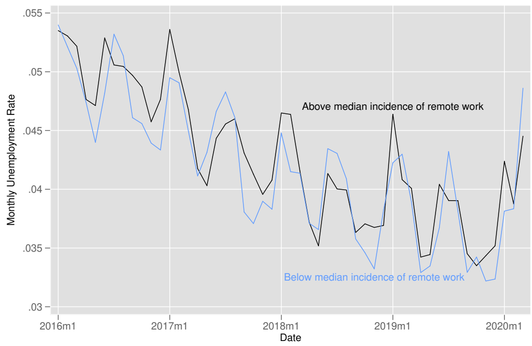
(c) Hours of Work.



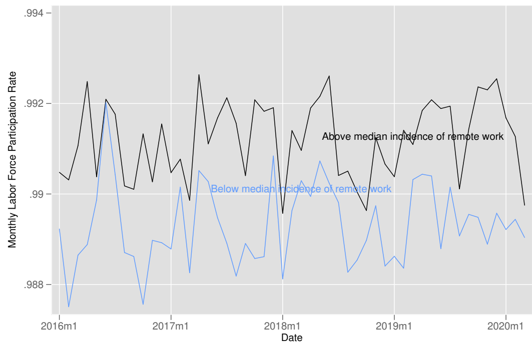
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

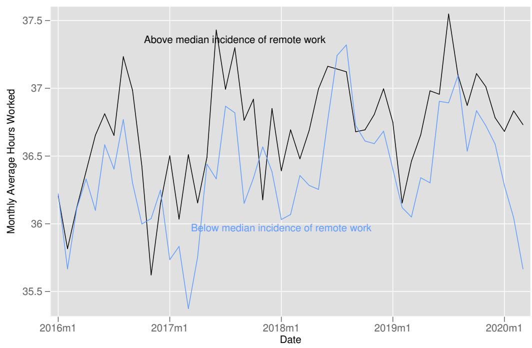
Figure 8: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Individuals in Occupations with High/Low pre-COVID-19 Remote Work Index.



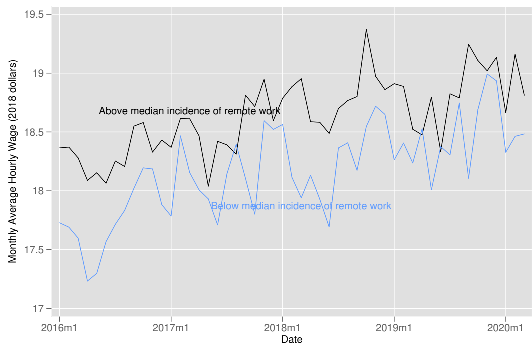
(a) Unemployment Rate.



(b) Labor Force Participation.



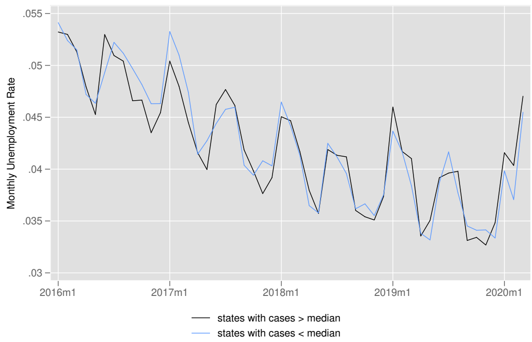
(c) Hours of Work.



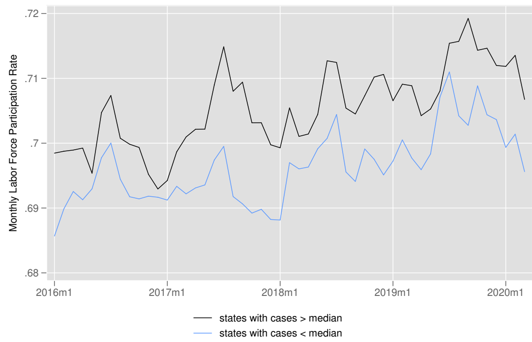
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 2020. Panel A plots the unemployment rate for individuals in occupations above and below the median for our index of pre-COVID-19 remoteness of work. Panel B plots the labor force participation for individuals in occupations above and below the median for our index of pre-COVID-19 remoteness of work. 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 pre-COVID-19 remoteness of 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 for individuals in occupations above and below the median for our index of pre-COVID-19 remoteness of work. 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.

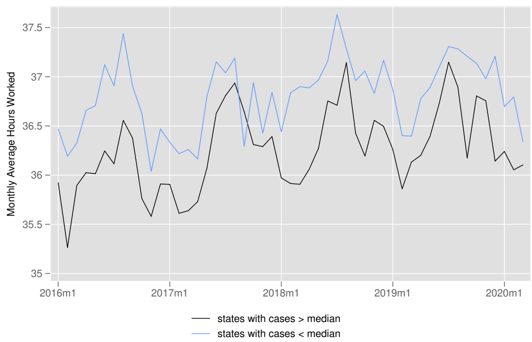
Figure 9: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by State COVID-19 Case Rate.



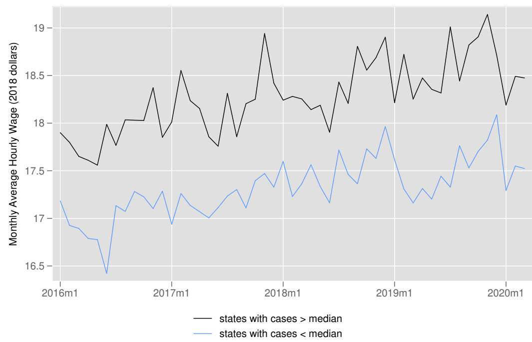
(a) Unemployment Rate.



(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 March 2020. Panel A plots the unemployment rate in states above and below the March 2020 median for cumulative number of known COVID-19 cases per 10,000 inhabitants. Panel B plots the labor force participationin states above and below the March 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 March 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 March 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.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Max	Min	Obs.
Unemployed	0.043	0.202	1.0	0.0	3,024,280
In labor force	0.705	0.456	1.0	0.0	4,310,529
Exposure to infection/disease index	21.954	24.266	100.0	0.0	3,043,122
Physical proximity to coworkers index	61.132	17.514	100.0	0.2	3,043,122
Remote work index	10.506	12.660	100.0	0.0	2,536,980
Real hourly wages in 2018 dollars	17.739	8.855	61.4	4.8	386,312
Weekly hours usually worked (all jobs)	38.997	12.658	198.0	1.0	2,799,585

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.

Table 2: COVID-19 and Labor Market Outcomes: National-Level

	Unemployed			In Labor Force		
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	0.00995	0.0102	0.0104	-0.00700	-0.00695	-0.00767
	(0.00109)	(0.00105)	(0.00103)	(0.00235)	(0.00212)	(0.00222)
n	3,024,280	3,024,280	3,024,280	4,310,529	4,310,529	4,310,529
	Hourly Wage			Hours of Work		
Post COVID	0.234	0.163	0.0755	-0.456	-0.518	-0.541
	(0.188)	(0.170)	(0.179)	(0.0890)	(0.0908)	(0.0862)
n	386,312	386,312	386,312	2,799,585	2,799,585	2,799,585
Individual Charact.	No	Yes	Yes	No	Yes	Yes
Education	No	No	Yes	No	No	Yes
Interview Type FE	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	No	Yes	Yes
Month FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes
Region × Year FE	No	No	Yes	No	No	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, columns 1–3, the dependent variable is a dummy for whether the individual is unemployed. In the top panel, columns 4–6, 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 1–3, 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 4–6, 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 month of March 2020. 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–March 2020.

Table 3: COVID-19 COVID-19-related Absences, Layoffs and Involuntary Part-time

		COVID-19 Related Unemployment	
	(1)	(2)	(3)
Post COVID	0.153	0.150	0.151
	(0.012)	(0.012)	(0.012)
n	123,097	123,097	123,097
		COVID-19 Related Reduced Hours	
Post COVID	0.049	0.047	0.047
	(0.007)	(0.007)	(0.007)
n	632,406	632,406	632,406
		COVID-19 Related Absences	
Post COVID	0.190	0.191	0.194
	(0.021)	(0.021)	(0.021)
n	101,598	101,598	101,598
Individual Charact.	No	Yes	Yes
Education	No	No	Yes
Interview Type FE	No	Yes	Yes
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region × Year FE	No	No	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. *Post COVID* is a dummy that is equal to one for the month of March 2020. 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–March 2020.

Table 4: The Impacts of COVID-19: Exposure, Proximity and Remote Work

			Unemployed			
	Exposure		Proximity		Remote Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	0.0138	0.0127	0.0071	0.0084	0.0146	0.0142
	(0.0011)	(0.0012)	(0.0039)	(0.0016)	(0.0013)	(0.0014)
Index	-0.000140		0.000047		-0.000051	
	(0.000010)		(0.000024)		(0.000027)	
Index × Post	-0.000093		0.000077		-0.0184	
	(0.000032)		(0.000057)		(0.0064)	
Index Dummy		-0.0033		0.0073		-0.0024
		(0.0005)		(0.0007)		(0.0006)
Index Dummy × Post		-0.0025		0.0091		-0.0029
		(0.0025)		(0.0026)		(0.0022)
n	3,012,371	3,012,371	3,012,371	3,012,371	2,511,881	2,511,881
			In Labor Force			
	Exposure		Proximity		Remote Work	
Post COVID	-0.000009	0.00014	0.000910	-0.00071	-0.00103	-0.00003
	(0.00079)	(0.00081)	(0.00184)	(0.00073)	(0.000893)	(0.00101)
Index	-0.0000032		-0.000023		0.000012	
	(0.0000022)		(0.000004)		(0.000006)	
Index × Post	-0.000026		-0.000025		0.00326	
	(0.000020)		(0.000033)		(0.00439)	
Index Dummy		-0.0012		-0.0020		0.0009
		(0.0002)		(0.00013)		(0.0002)
Index Dummy × Post		-0.0020		0.00033		-0.0013
		(0.0012)		(0.0015)		(0.0014)
n	3,043,122	3,043,122	3,043,122	3,043,122	2,536,980	2,536,980
Individual Charact.	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × 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. 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. *Post COVID* is a dummy that is equal to one for the month of March 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–March 2020.

Table 5: The Impacts of COVID-19: Exposure, Proximity and Remote Work

	Hourly Wages					
	Exposure		Proximity		Remote Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	-0.111	-0.132	-0.384	-0.0408	-0.0619	-0.118
	(0.241)	(0.190)	(0.509)	(0.198)	(0.232)	(0.239)
Index	0.0263		-0.00374		-0.0106	
	(0.00148)		(0.00212)		(0.00279)	
Index × Post	0.00448		0.00578		0.0383	
	(0.00541)		(0.00742)		(1.485)	
Index Dummy		-0.345		-0.899		-0.142
		(0.0430)		(0.0537)		(0.0593)
Index Dummy × Post		0.278		0.0470		0.145
		(0.205)		(0.243)		(0.302)
n	360,212	360,212	360,212	360,212	299,902	299,902
	Hours of Work					
	Exposure		Proximity		Remote Work	
Post COVID	-0.350	-0.305	0.244	0.120	-0.465	-0.524
	(0.241)	(0.227)	(0.726)	(0.245)	(0.255)	(0.256)
Index	-0.0136		-0.0389		-0.0120	
	(0.00152)		(0.00288)		(0.00251)	
Index × Post	0.00782		-0.00643		1.750	
	(0.00543)		(0.0103)		(1.624)	
Index Dummy		-1.619		-2.484		0.359
		(0.0542)		(0.102)		(0.0511)
Index Dummy × Post		0.343		-0.635		0.477
		(0.254)		(0.358)		(0.238)
n	360,212	360,212	360,212	360,212	299,902	299,902
Individual Charact.	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × 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. 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. *Post COVID* is a dummy that is equal to one for the month of March 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–March 2020.

Table 6: COVID-19-related Absences, Layoffs and Involuntary Part-time: Exposure, Proximity and Remote Work

	Exposure		Unemployed Proximity		Remote Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID	0.117	0.131	0.0197	0.121	0.162	0.170
	(0.0173)	(0.0180)	(0.0399)	(0.0163)	(0.0178)	(0.0206)
Index	0.0000875		0.00125		-0.000250	
	(0.000111)		(0.000313)		(0.000184)	
Index × Post	0.00211		0.00215		-0.00429	
	(0.000599)		(0.000627)		(0.104)	
Index Dummy		-0.0161		0.0463		-0.00351
		(0.00496)		(0.00566)		(0.00507)
Index Dummy × Post		0.0761		0.0661		-0.0176
		(0.0279)		(0.0232)		(0.0272)
n	114,220	114,220	114,220	114,220	94,501	94,501
	Exposure		Reduced Hours Proximity		Remote Work	
Post COVID	0.0601	0.0601	0.0698	0.0552	0.0560	0.0524
	(0.00796)	(0.00843)	(0.0156)	(0.00859)	(0.00864)	(0.00813)
Index	-0.000227		-0.000167		-0.000652	
	(0.0000374)		(0.0000497)		(0.0000774)	
Index × Post	-0.000438		-0.000321		-0.0224	
	(0.000178)		(0.000198)		(0.0280)	
Index Dummy		-0.0220		-0.0141		0.00440
		(0.00177)		(0.00153)		(0.00190)
Index Dummy × Post		-0.0246		-0.0120		0.00275
		(0.0119)		(0.00797)		(0.00736)
n	674,907	674,907	674,907	674,907	559,309	559,309
	Exposure		Absences Proximity		Remote Work	
Post COVID	0.210	0.192	0.121	0.160	0.204	0.217
	(0.0227)	(0.0226)	(0.0329)	(0.0208)	(0.0282)	(0.0270)
Index	-0.000396		-0.0000171		0.00201	
	(0.0000639)		(0.0000875)		(0.000140)	
Index × Post	-0.000507		0.00114		0.0716	
	(0.000395)		(0.000553)		(0.101)	
Index Dummy		-0.0148		0.00349		0.0219
		(0.00364)		(0.00246)		(0.00439)
Index Dummy × Post		0.0103		0.0707		-0.0118
		(0.0252)		(0.0245)		(0.0269)
n	106,719	106,719	106,719	106,719	88,703	88,703
Individual Charact.	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × 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. 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. *Post COVID* is a dummy that is equal to one for the month of March 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– March 2020.

Table 7: COVID-19 Cases and Labor Market Outcomes: State-Level

	Unemployed				In Labor Force			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative Cases per 10,000	0.0224	0.0224	0.0233	0.0754	-0.0124	-0.0123	-0.0303	-0.0716
	(0.00767)	(0.00758)	(0.00741)	(0.0235)	(0.00775)	(0.00683)	(0.00863)	(0.0197)
Cumulative Cases per 10,000 Squared				-0.0801				0.0636
				(0.0274)				(0.0239)
n	3,024,280	3,024,280	3,024,280	3,024,280	4,310,529	4,310,529	4,310,529	4,310,529
	Hourly Wage				Hours of Work			
Cumulative Cases per 10,000	0.635	0.864	0.682	1.007	-1.366	-1.277	-1.436	-0.412
	(0.656)	(0.482)	(0.489)	(1.915)	(0.523)	(0.449)	(0.451)	(1.737)
Cumulative Cases per 10,000 Squared				-0.514				-1.609
				(2.267)				(2.074)
n	386,312	386,312	386,312	386,312	360,212	360,212	360,212	360,212
Individual Charact.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Education	No	No	Yes	Yes	No	No	Yes	Yes
Interview Type FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Data from the Current Population Survey. Robust standard errors are in parentheses, adjusted for clustering by state. In the top panel, columns 1–3, the dependent variable is a dummy for whether the individual is unemployed. In the top panel, columns 4–6, 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 1–3, 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 4–6, 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 FE. Columns 2, 3, 5 and 6 add month and interview type fixed effects and the following demographic controls: gender, age, marital status and race. Columns 3 and 6 add education dummies, year fixed effects and four Census region × year fixed effects. The time period is January 2016–March 2020.

Table 8: COVID-19 Cases and Exposure, Proximity and Remote Work: State-Level

	Exposure		Proximity		Remote Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed						
Cumulative Cases per 10,000	0.0384	0.0358	0.00578	0.0122	0.0301	0.0375
	(0.0130)	(0.0130)	(0.0131)	(0.00852)	(0.0117)	(0.0116)
Index	-0.000141		0.0000481		-0.0000547	
	(0.0000104)		(0.0000240)		(0.0000266)	
Index × Cases	-0.000442		0.000376		-0.0209	
	(0.000172)		(0.000222)		(0.0209)	
Index Dummy		-0.00329		0.00736		-0.00245
		(0.000460)		(0.000672)		(0.000615)
Index Dummy × Cases		-0.0200		0.0443		-0.0194
		(0.0102)		(0.0135)		(0.00658)
n	3,012,371	3,012,371	3,012,371	3,012,371	2,511,881	2,511,881
In Labor Force	Exposure		Proximity		Remote Work	
Cumulative Cases per 10,000	0.00417	0.00216	0.0130	-0.000707	0.00113	0.00585
	(0.00319)	(0.00320)	(0.00440)	(0.00256)	(0.00299)	(0.00406)
Index	-0.00000331		-0.0000228		0.0000121	
	(0.00000199)		(0.00000351)		(0.00000603)	
Index × Cases	-0.000180		-0.000213		0.00798	
	(0.0000970)		(0.0000829)		(0.0221)	
Index Dummy		-0.00120		-0.00199		0.000855
		(0.000138)		(0.000132)		(0.000176)
Index Dummy × Cases		-0.00552		0.00228		-0.00750
		(0.00638)		(0.00345)		(0.00966)
n	3,043,122	3,043,122	3,043,122	3,043,122	2,536,980	2,536,980
Individual Charact.	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × 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. 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–March 2020.

Table 9: COVID-19 Cases and Exposure, Proximity and Remote Work: State-Level

	Hourly Wages					
	Exposure		Proximity		Remote Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Cases per 10,000	0.236	0.0488	-1.872	-0.0606	0.550	0.0727
	(1.034)	(0.744)	(1.813)	(0.643)	(0.740)	(0.700)
Index	0.0264		-0.00369		-0.0105	
	(0.00151)		(0.00213)		(0.00274)	
Index × Cases	0.00934		0.0376		-5.721	
	(0.0309)		(0.0258)		(4.122)	
Index Dummy		-0.342		-0.901		-0.139
		(0.0440)		(0.0538)		(0.0600)
Index Dummy × Cases		1.143		1.234		0.0489
		(1.276)		(0.874)		(1.003)
n	360,212	360,212	360,212	360,212	299,902	299,902
	Hours of Work					
	Exposure		Proximity		Remote Work	
Cumulative Cases per 10,000	-1.107	-1.364	2.500	0.0336	-2.049	-1.845
	(0.823)	(0.586)	(3.132)	(0.801)	(0.725)	(0.672)
Index	-0.0134		-0.0389		-0.0118	
	(0.00151)		(0.00282)		(0.00249)	
Index × Cases	-0.00630		-0.0608		5.802	
	(0.0328)		(0.0509)		(4.721)	
Index Dummy		-1.613		-2.490		0.366
		(0.0547)		(0.101)		(0.0504)
Index Dummy × Cases		0.218		-3.303		0.785
		(1.370)		(1.123)		(0.929)
n	360,212	360,212	360,212	360,212	299,902	299,902
Individual Charact.	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × 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. 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–March 2020.

Appendix: NOT FOR PUBLICATION

5.1 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 A4 and A5) 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 $(= (4 - 1)/(5 - 1)) * 100)$.

5.2 Labor Market Outcomes by Major Occupation Groups

Appendix Figures A17–A38 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 March 2020. Personal care and service occupations were particularly hard hit and jumped from just under 3% unemployment in February to just under 7% in March. Food preparation and serving related occupations went from under 6% to over 9%. Likewise, most occupations saw a drop in labor force participation in March. Again, food preparation and serving was one of the largest fallers with about a 0.5 percentage point decline. Several other occupations (e.g. building a grounds cleaning and maintenance, management, community and social service occupations) experienced a similar shift. Across occupations, hours worked tended to fall, with Arts, Design, Entertainment, Sports, and Media occupations dropping just over 2 hours worked in March. Food preparation and serving also fell about 2 hours, while most other occupations saw declines of about an hour. Lastly, the response from February to March of hourly wages was a bit of a mixed bag. Production related occupations saw declines of about \$0.25 while construction and extraction occupations saw losses of over \$1. However, some occupations (e.g. education, training, and library occupations; arts, design, entertainment, sports, and media; and building and grounds cleaning and maintenance) saw increases in hourly wages.

Of particular interest are the labor market outcomes for health workers, found in Appendix Figures A26 and A27. Unemployment actually fell for healthcare and support occupations but increased modestly for healthcare practitioners and technical occupations. The labor force participation rates fell by around 0.2 percentage points for both occupations. Hours of work increased by about half an hour for healthcare support occupations while practitioners and technical occupations saw a jump of nearly an hour. Wages increased slightly for healthcare practitioners and technical occupations while healthcare support occupations saw wages fall by about $0.50.

Figure A1: Timeline in the United States

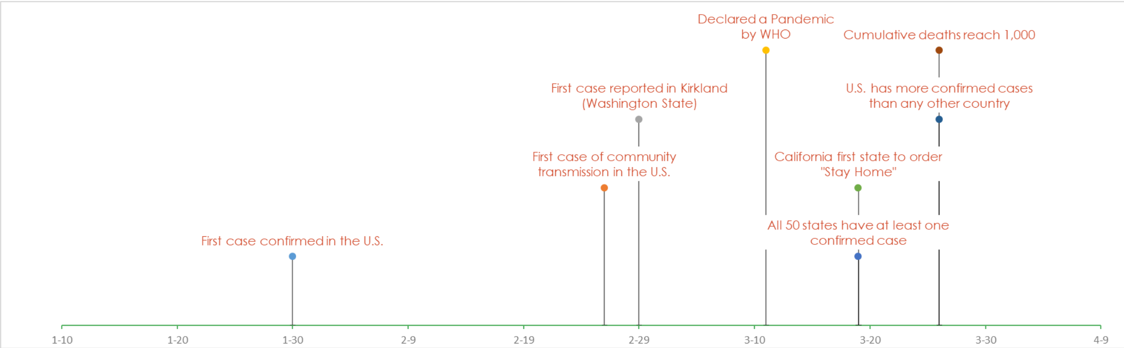


Figure A2: Number of States with at Least One Confirmed Case

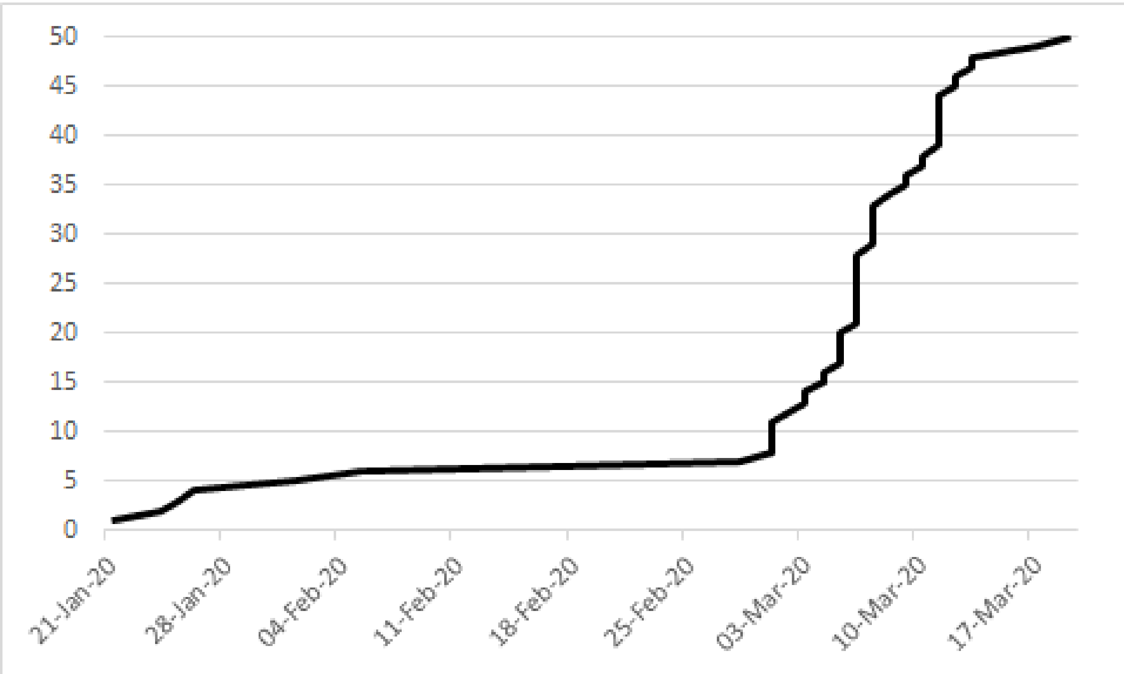


Figure A3: Number of States with at Least One Death

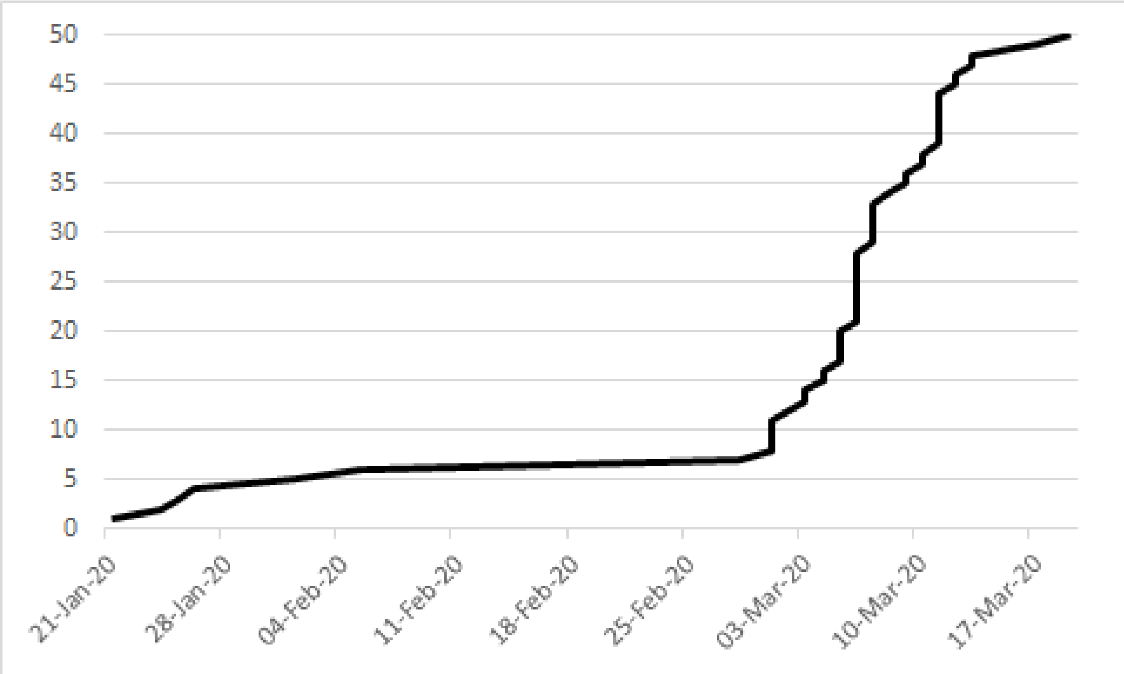
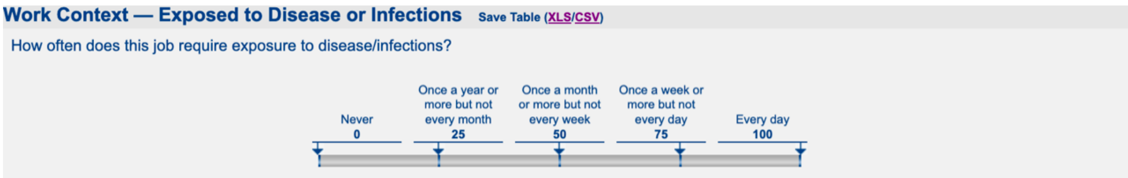
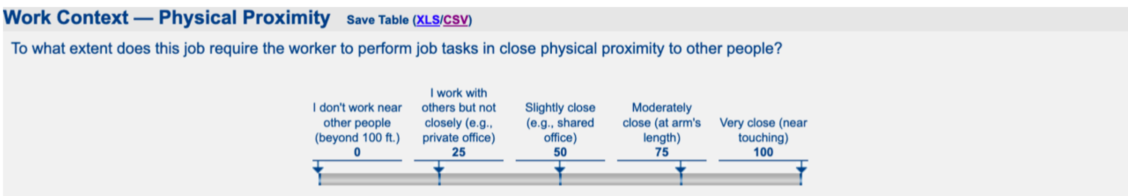


Figure A4: O*NET Survey Question Used for Exposure to Disease



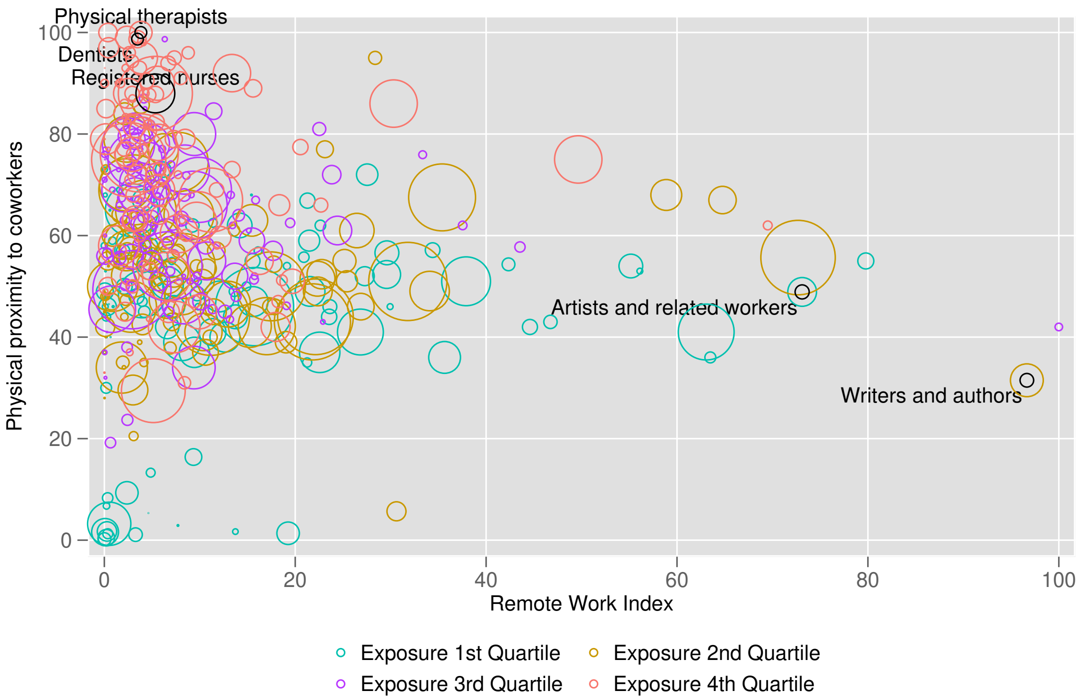
Notes: Survey question asking "How often does this job require exposure to disease/infections?" with five possible answers: (1) Never, (2) Once a year or more but not every month, (3) Once a month or more but not every week, (4) Once a week or more but not every day, and (5) Every day.

Figure A5: O*NET Survey Question Used for Physical Proximity



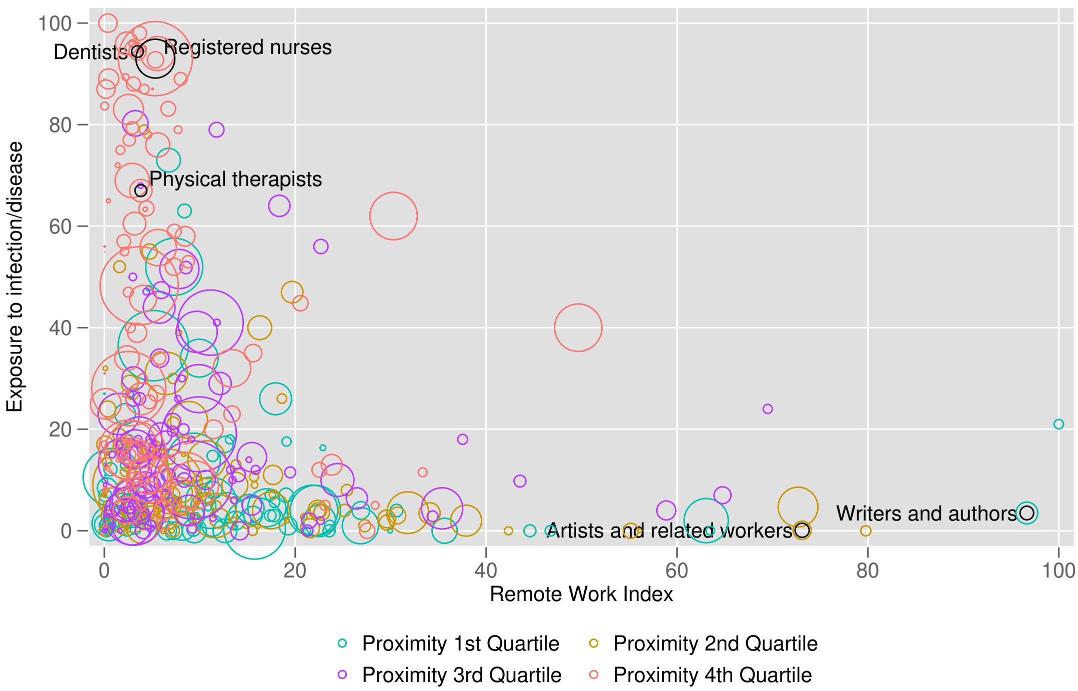
Notes: Survey question asking "How physically close to other people are you when you perform your current job?" with five possible responses: (1) I don't work near other people(beyond 100 ft.), (2) I work with others but not closely (e.g., private office), (3) Slightly close (e.g., shared office), (4)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

Figure A6: Physical Proximity, Exposure to the Disease and Remote Work by Occupation



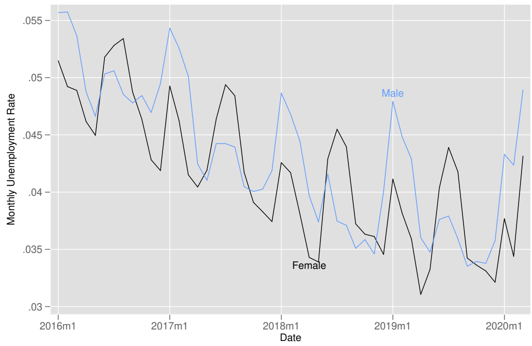
Notes: Each circle represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's value of the remote work index we constructed. The further to the right, the more commonly this occupation is done at home. The y-axis plots each occupation's physical proximity to coworkers, measured by O*NET's index. The further up, the closer in proximity employees in that occupation work with their coworkers. The color of the circles corresponds to the quartile of each occupation in the exposure to infection and disease index, also measure by O*NET. Occupations in the first quartile are less frequently exposed while those in the fourth quartile are more commonly exposed.

Figure A7: Physical Proximity, Exposure to the Disease and Remote Work by Occupation

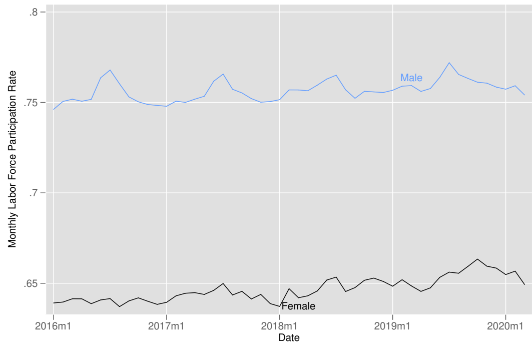


Notes: Each circle represents an occupation. The size of each circle represents the number of CPS respondents employed in that occupation–the larger the circle, the greater the number of people employed in that occupation. The x-axis plots each occupation's value of the remote work index we constructed. The further to the right, the more commonly this occupation is done at home. 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 quartile of each occupation in the physical proximity to coworkers. Occupations in the first quartile work farther away from others while those in the fourth quartile work more closely with others.

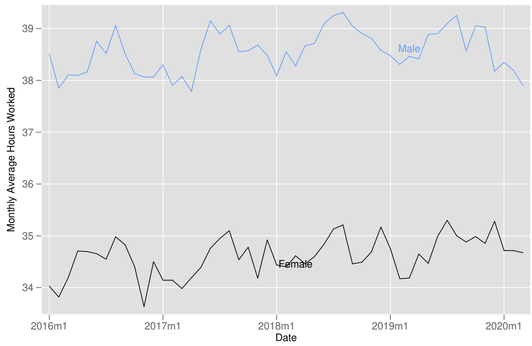
Figure A8: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Gender.



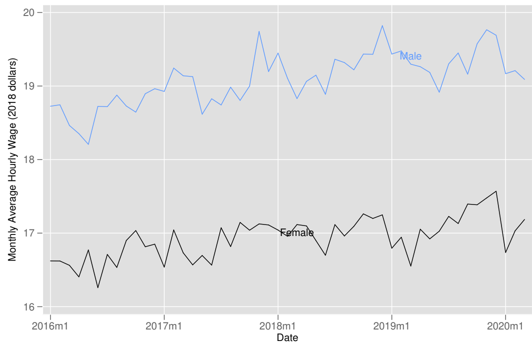
(a) Unemployment Rate.



(b) Labor Force Participation.



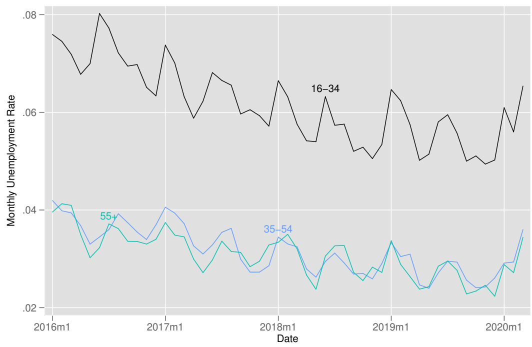
(c) Hours of Work.



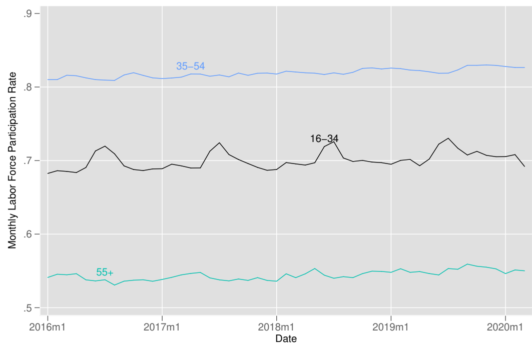
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

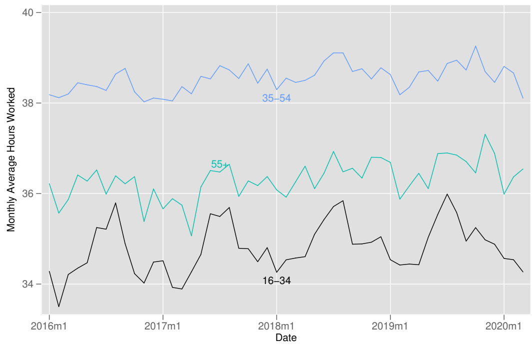
Figure A9: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Age Groups.



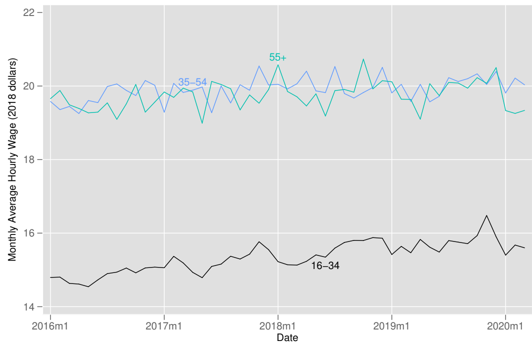
(a) Unemployment Rate.



(b) Labor Force Participation.



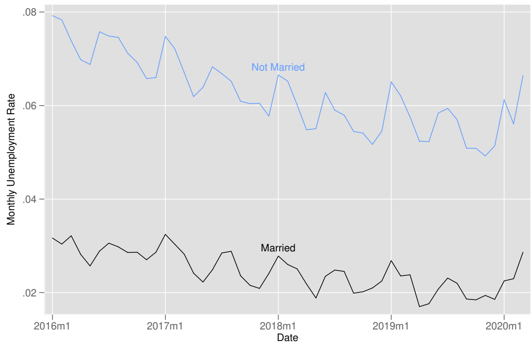
(c) Hours of Work.



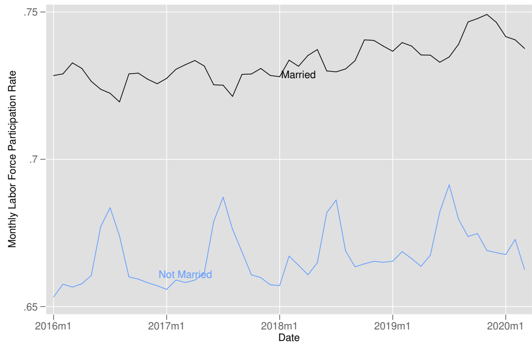
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

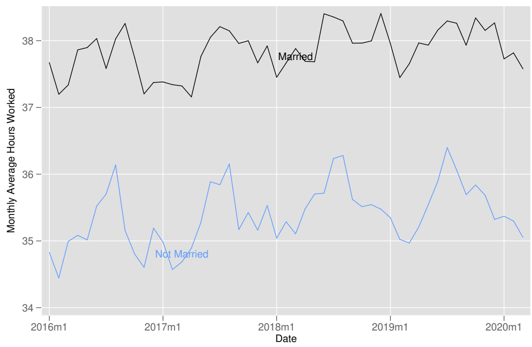
Figure A10: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Marital Status.



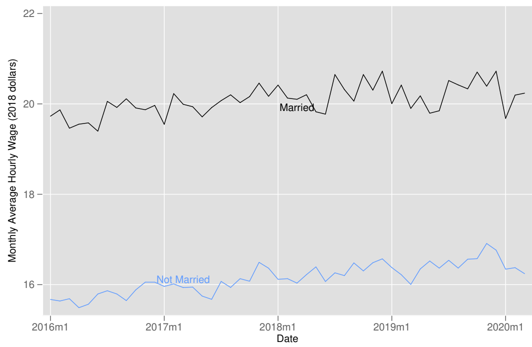
(a) Unemployment Rate.



(b) Labor Force Participation.



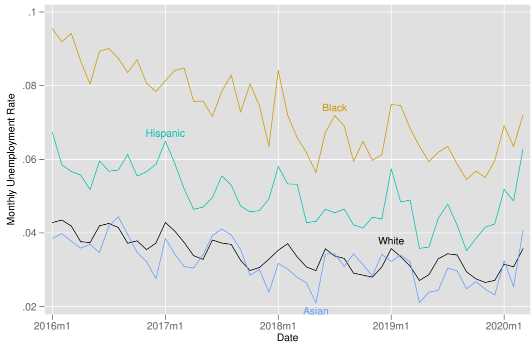
(c) Hours of Work.



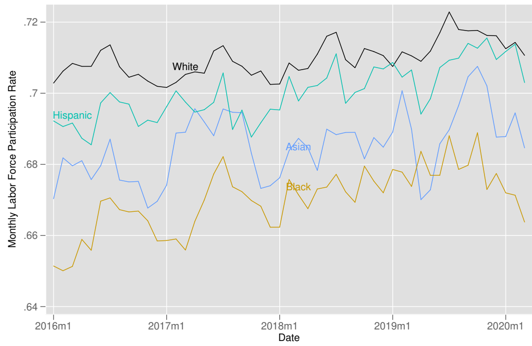
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

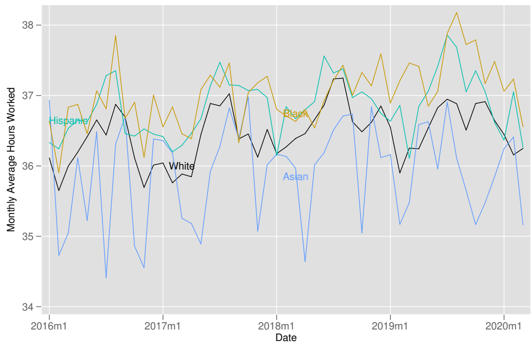
Figure A11: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Race.



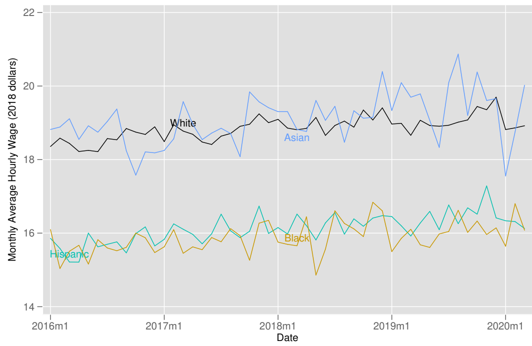
(a) Unemployment Rate.



(b) Labor Force Participation.



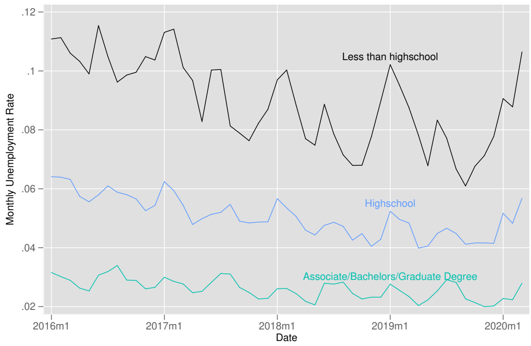
(c) Hours of Work.



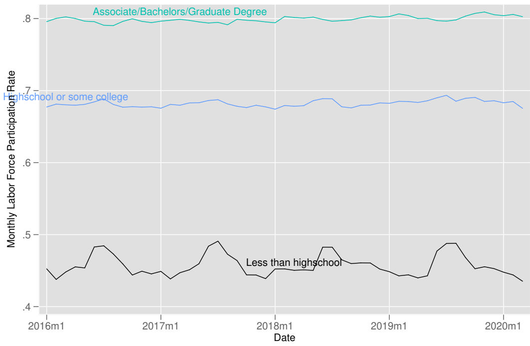
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

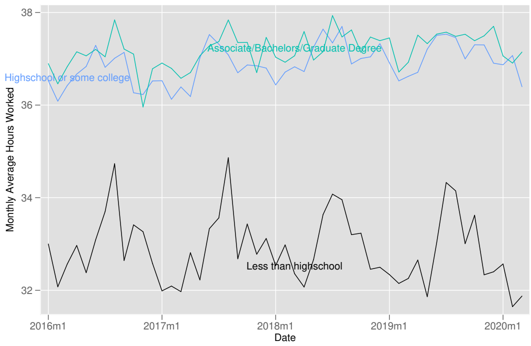
Figure A12: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Education Status.



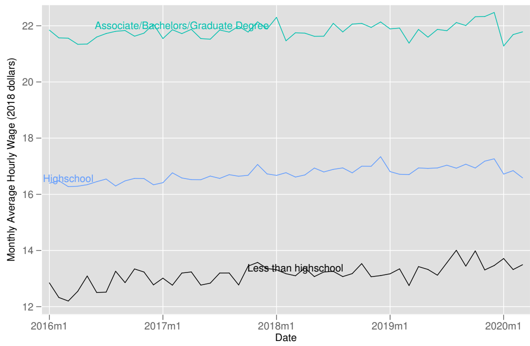
(a) Unemployment Rate.



(b) Labor Force Participation.



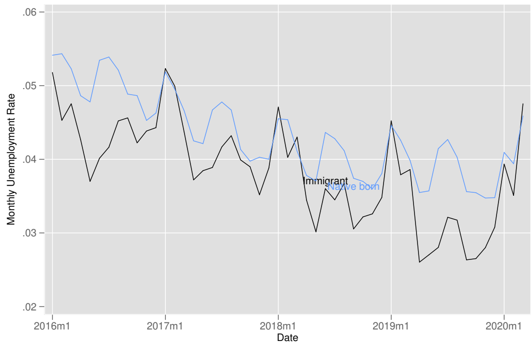
(c) Hours of Work.



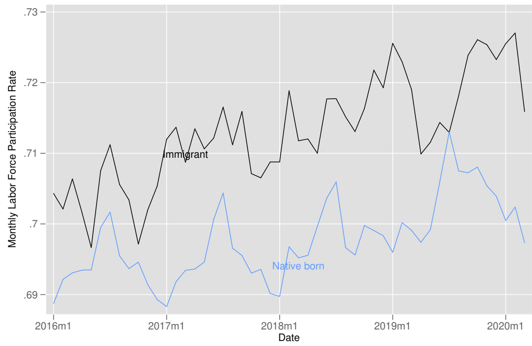
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

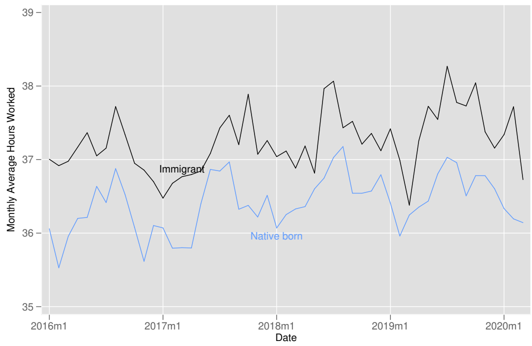
Figure A13: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Immigration Status.



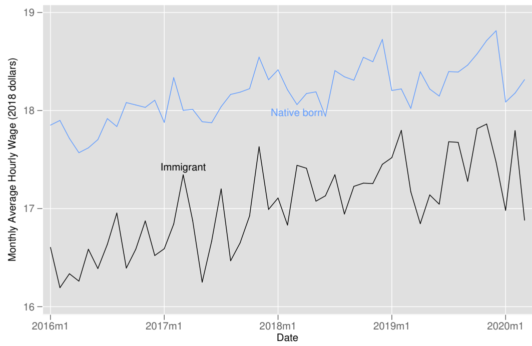
(a) Unemployment Rate.



(b) Labor Force Participation.



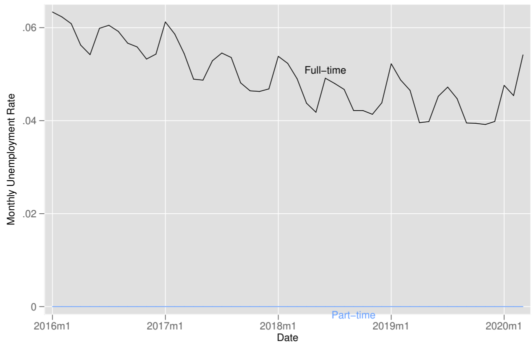
(c) Hours of Work.



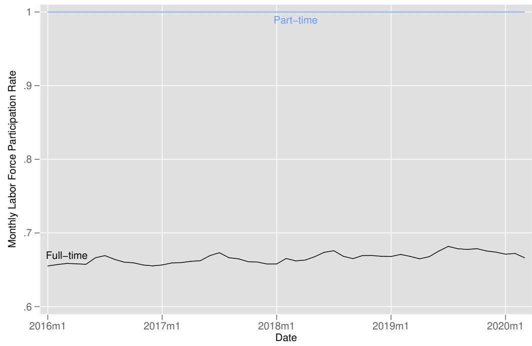
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

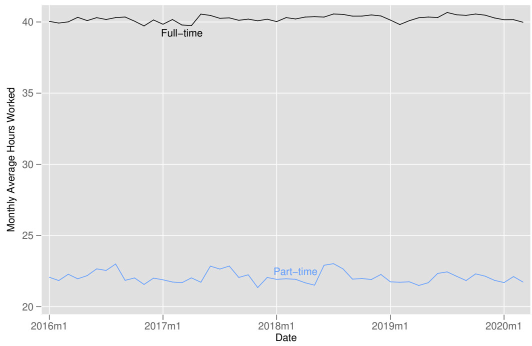
Figure A14: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Full-Time and Part-Time Workers.



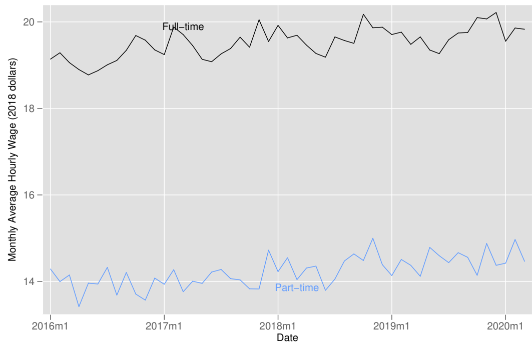
(a) Unemployment Rate.



(b) Labor Force Participation.



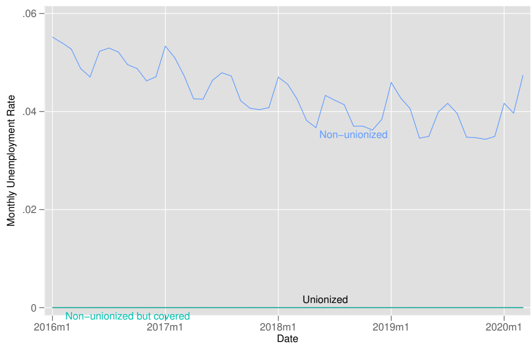
(c) Hours of Work.



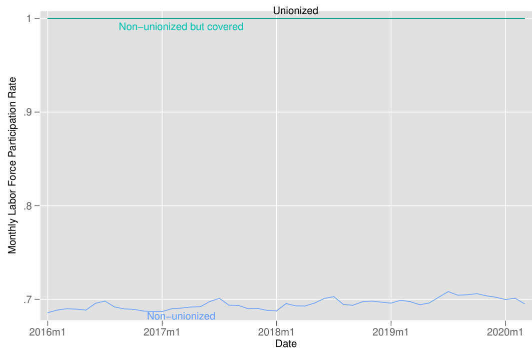
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

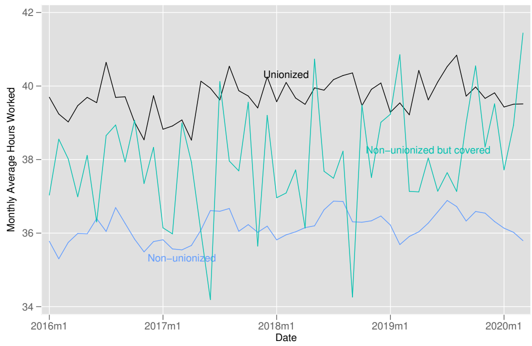
Figure A15: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages by Union Status.



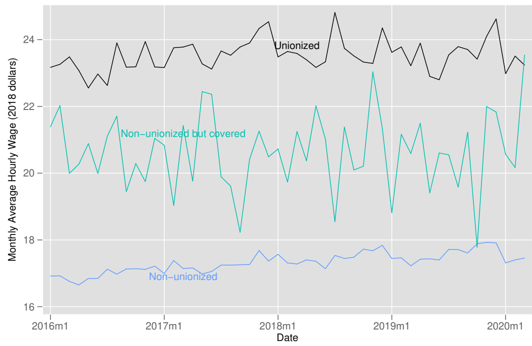
(a) Unemployment Rate.



(b) Labor Force Participation.



(c) Hours of Work.

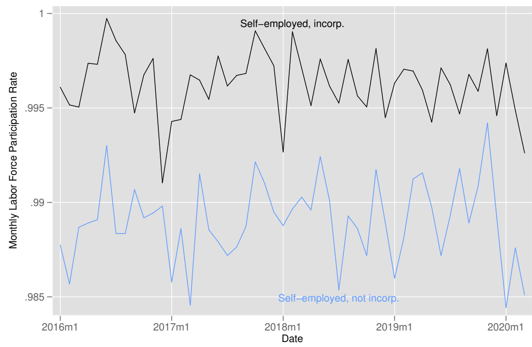


(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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 A16: Unemployment Rate, Labor Force Participation, and Hours of Work by Self-Employment Incorporated and Unincorporated.

(a) Unemployment Rate.

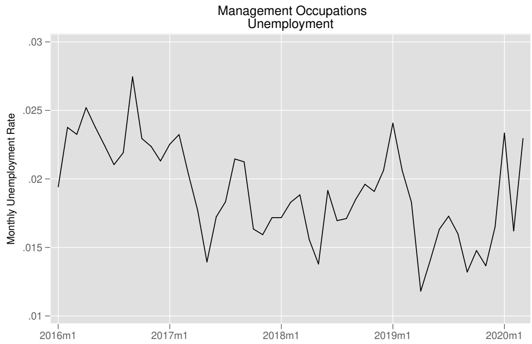


(b) Labor Force Participation.

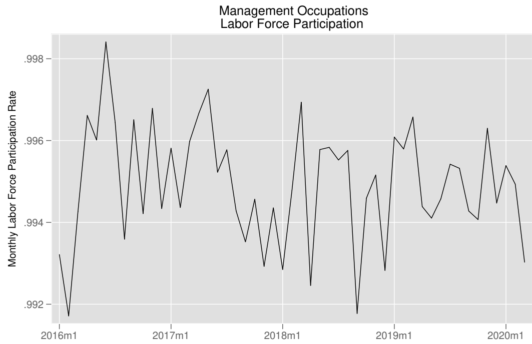
(c) Hours of Work.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 2020. Panel A plots the unemployment rate for self-employed individuals, incorporated and self-employed individuals, unicorporated. 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.

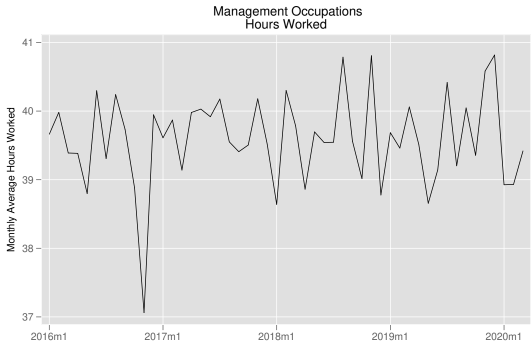
Figure A17: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Management Occupations.



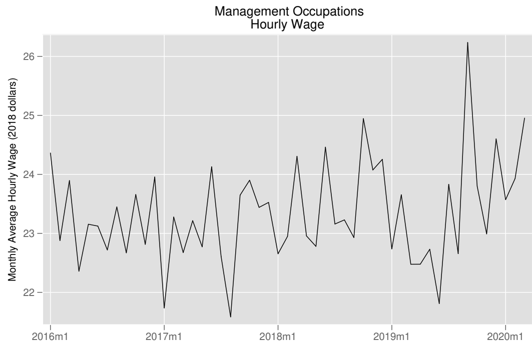
(a) Unemployment Rate.



(b) Labor Force Participation.



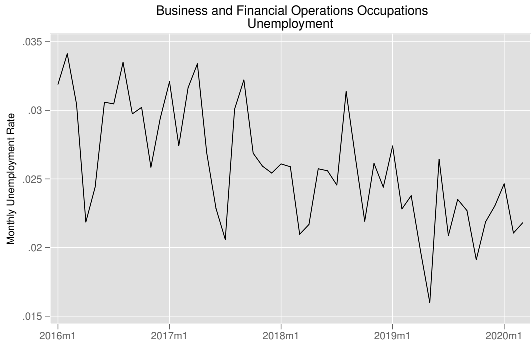
(c) Hours of Work.



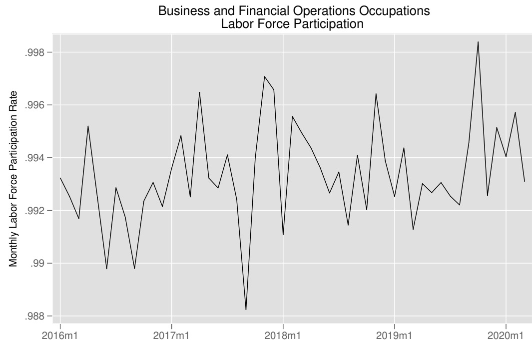
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

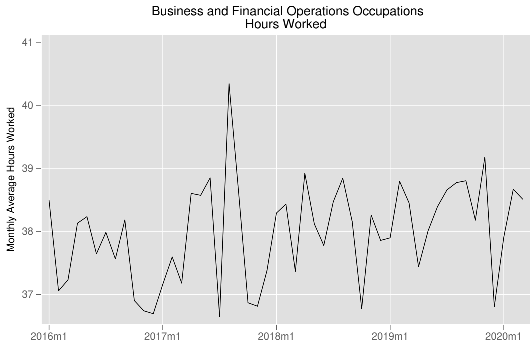
Figure A18: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Business and Financial Operations Occupations".



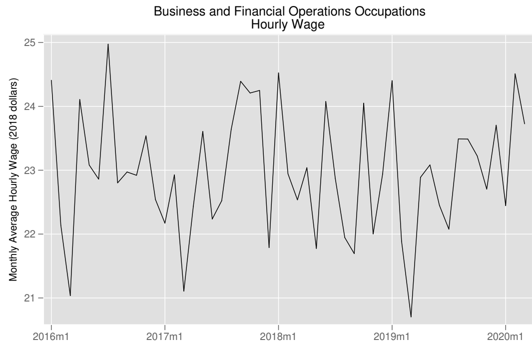
(a) Unemployment Rate.



(b) Labor Force Participation.



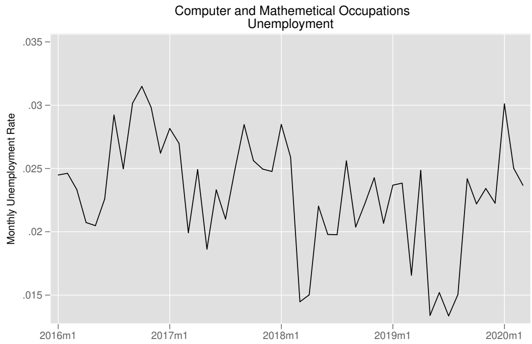
(c) Hours of Work.



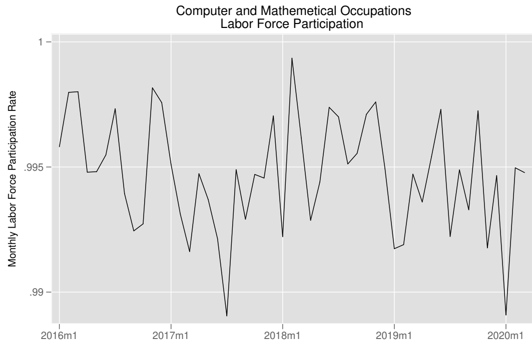
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

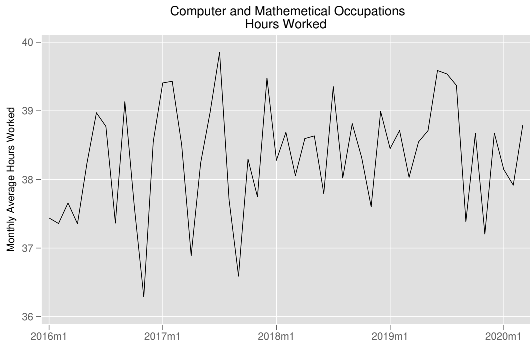
Figure A19: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Computer and Mathemetical Occupations.



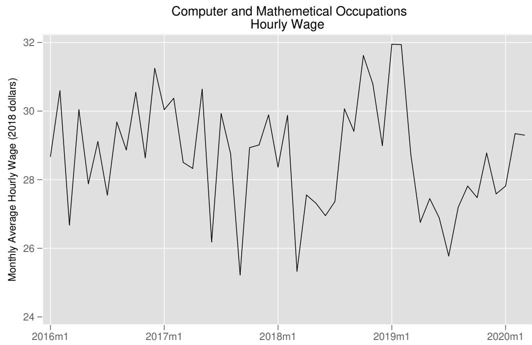
(a) Unemployment Rate.



(b) Labor Force Participation.



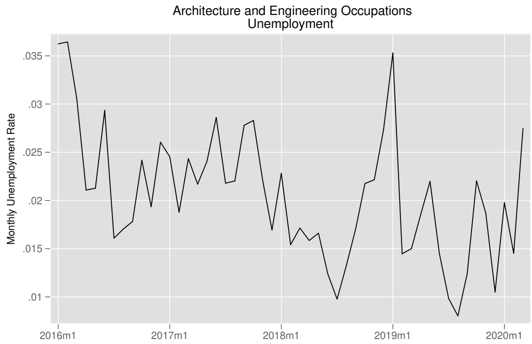
(c) Hours of Work.



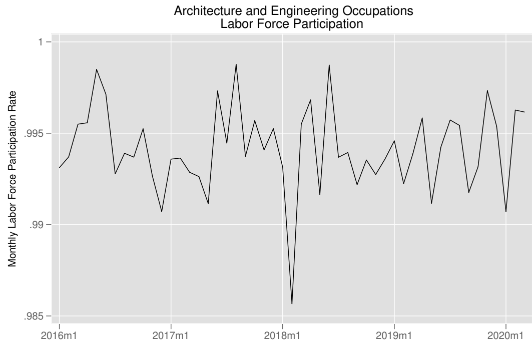
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

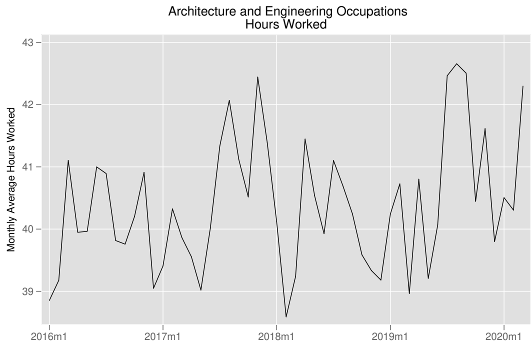
Figure A20: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Architecture and Engineering Occupations.



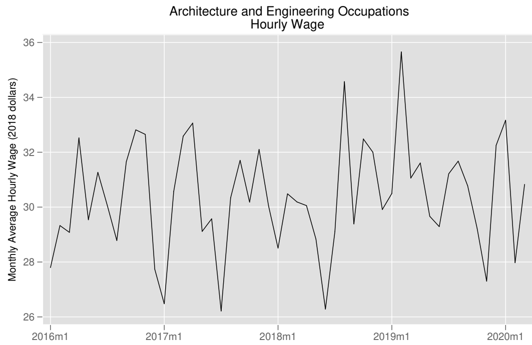
(a) Unemployment Rate.



(b) Labor Force Participation.



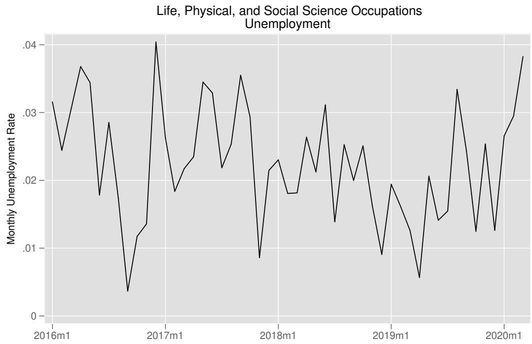
(c) Hours of Work.



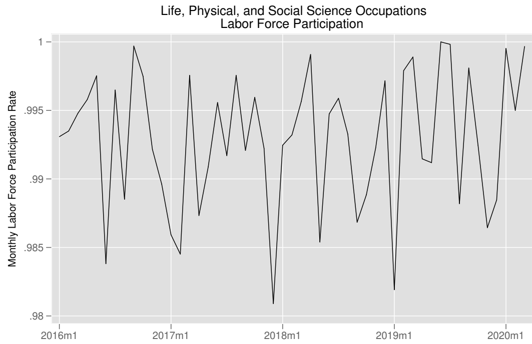
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

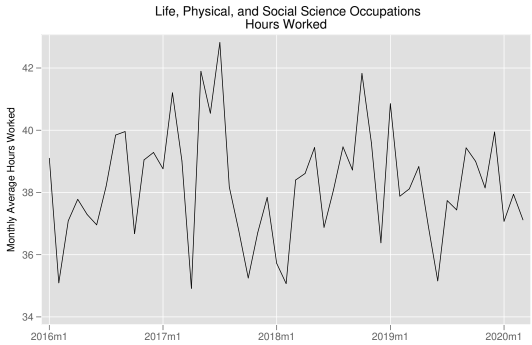
Figure A21: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Life, Physical, and Social Science Occupations.



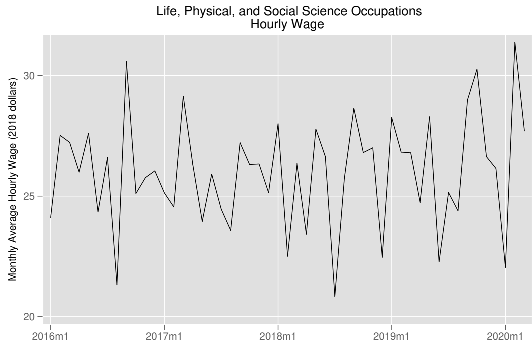
(a) Unemployment Rate.



(b) Labor Force Participation.



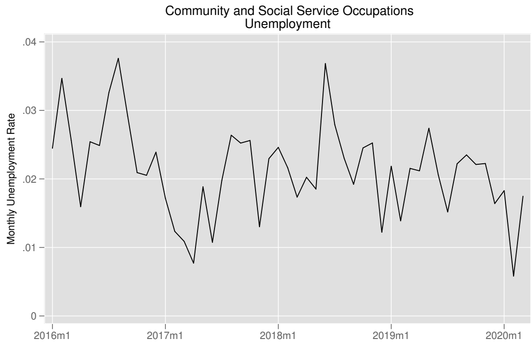
(c) Hours of Work.



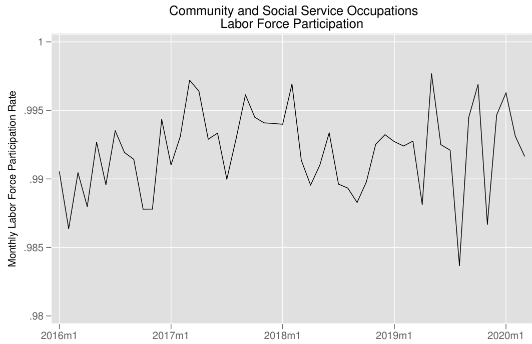
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

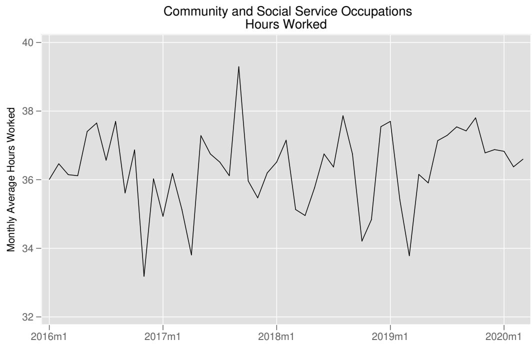
Figure A22: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Community and Social Service Occupations.



(a) Unemployment Rate.



(b) Labor Force Participation.

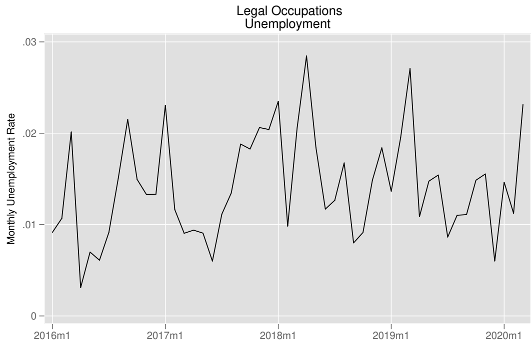


(c) Hours of Work.

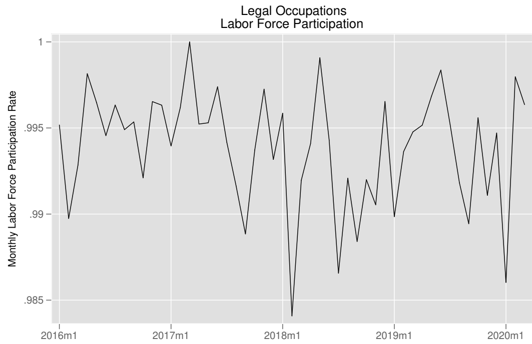
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

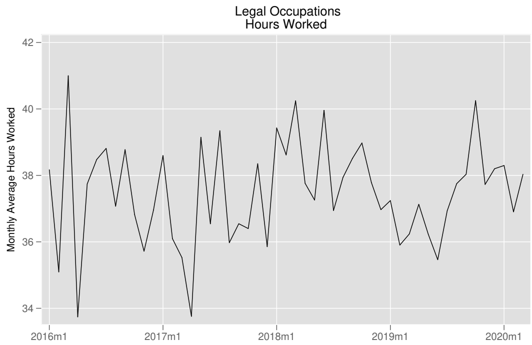
Figure A23: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Legal Occupations.



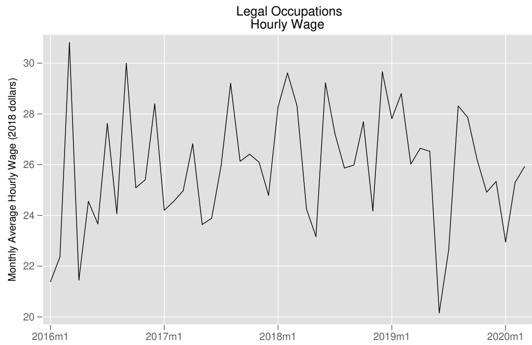
(a) Unemployment Rate.



(b) Labor Force Participation.



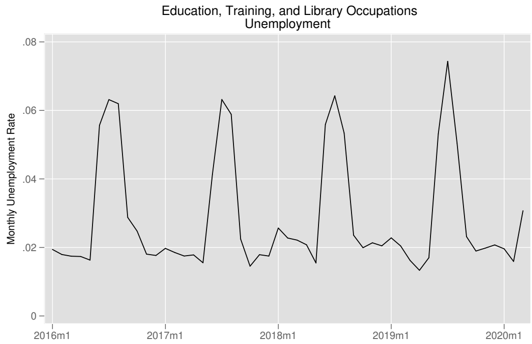
(c) Hours of Work.



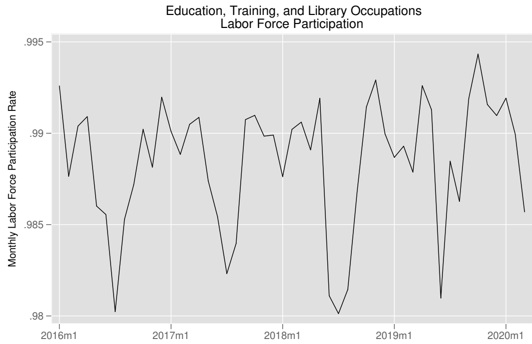
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

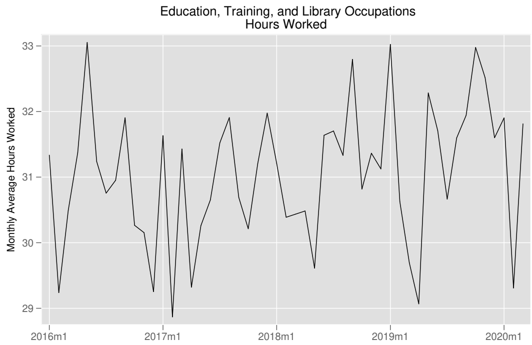
Figure A24: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Education, Training, and Library Occupations.



(a) Unemployment Rate.



(b) Labor Force Participation.



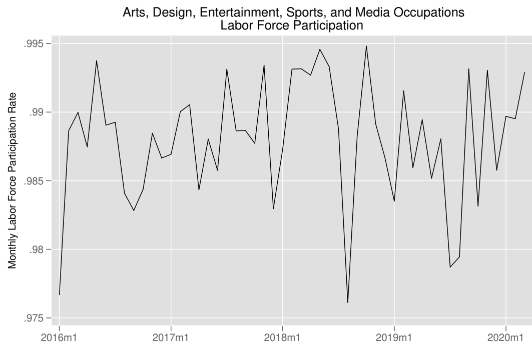
(c) Hours of Work.

(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

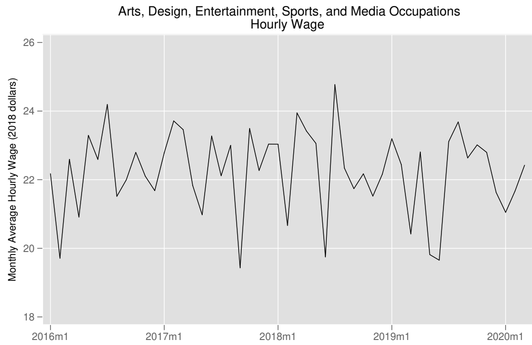
Figure A25: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Arts, Design, Entertainment, Sports, and Media Occupations.

(a) Unemployment Rate.



(b) Labor Force Participation.

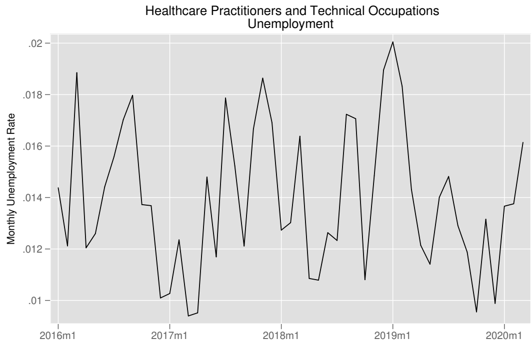
(c) Hours of Work.



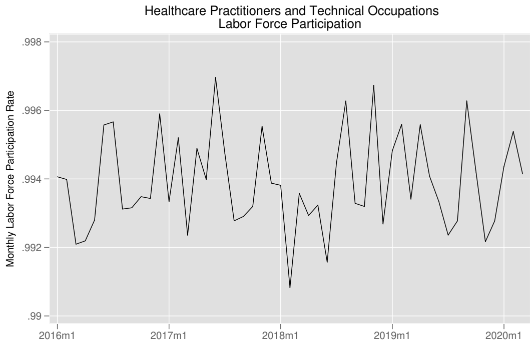
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

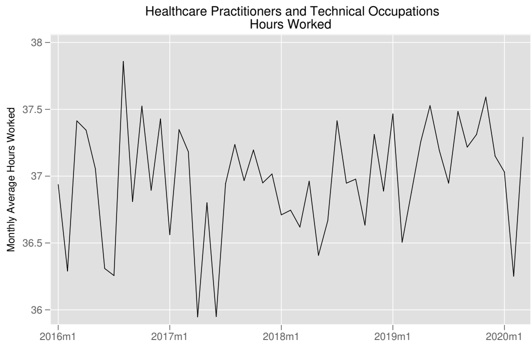
Figure A26: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Healthcare Practitioners and Technical Occupations.



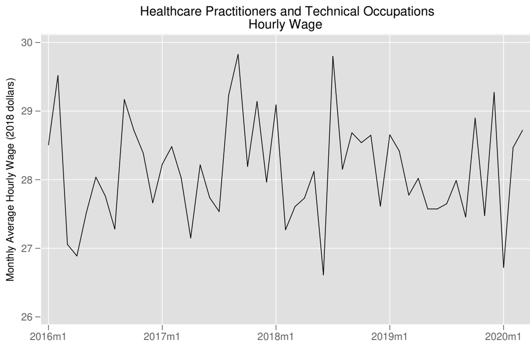
(a) Unemployment Rate.



(b) Labor Force Participation.



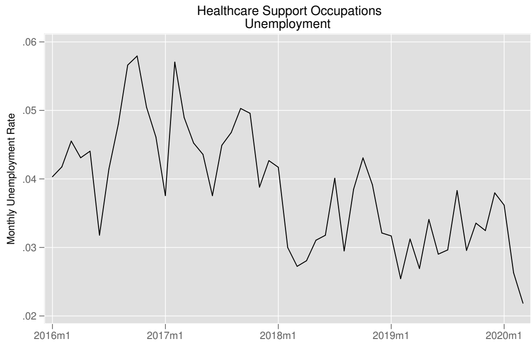
(c) Hours of Work.



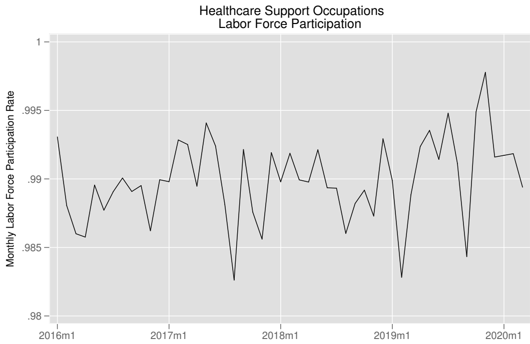
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

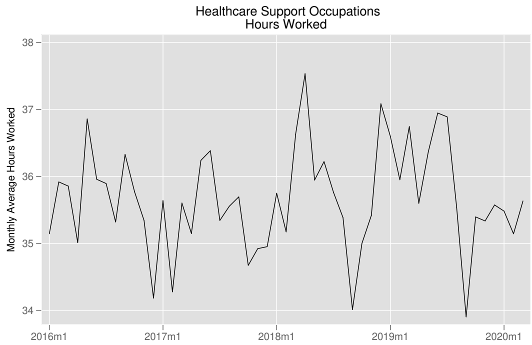
Figure A27: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Healthcare Support Occupations.



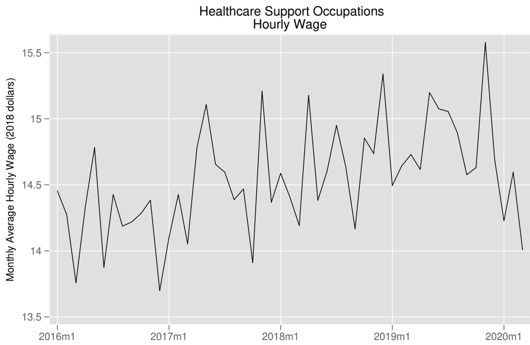
(a) Unemployment Rate.



(b) Labor Force Participation.



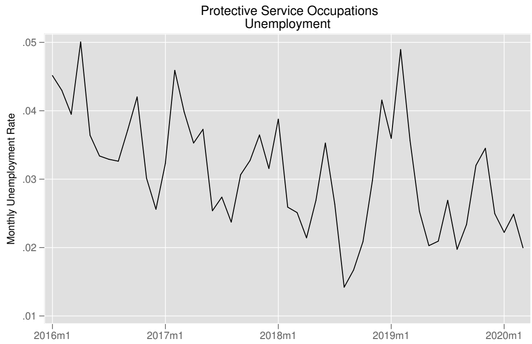
(c) Hours of Work.



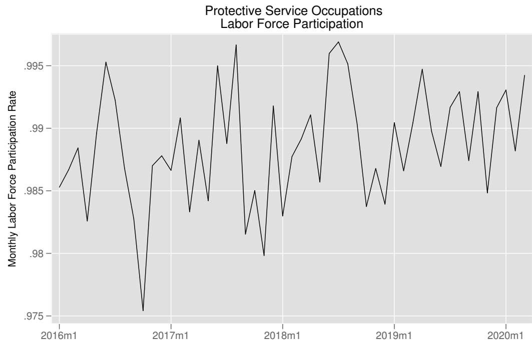
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

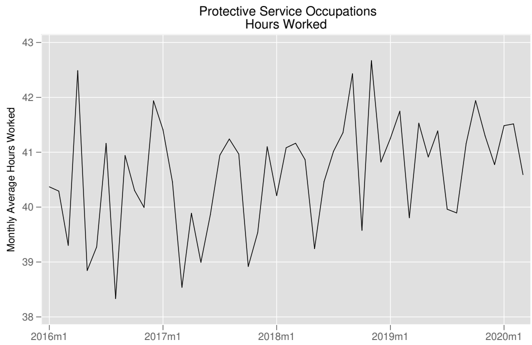
Figure A28: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Protective Service Occupations.



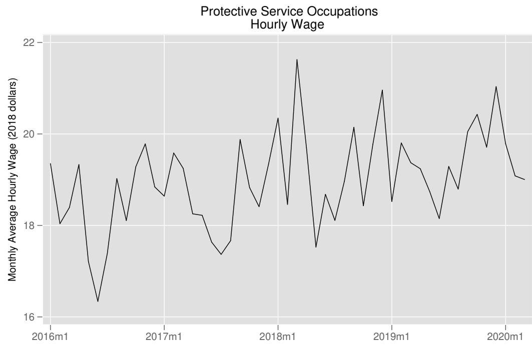
(a) Unemployment Rate.



(b) Labor Force Participation.



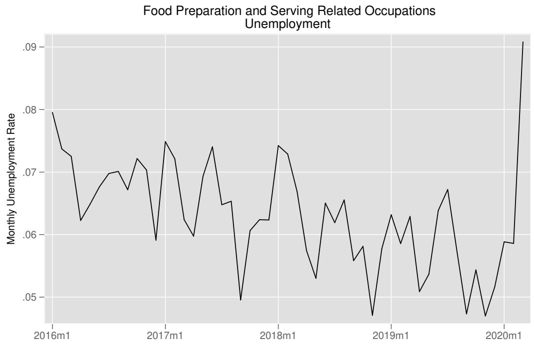
(c) Hours of Work.



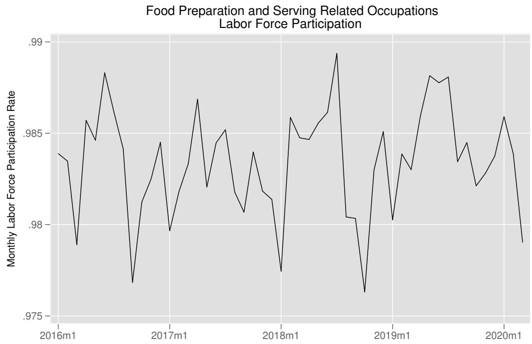
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

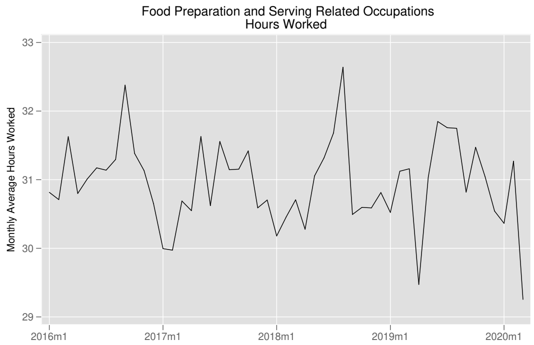
Figure A29: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Food Preparation and Serving Related Occupations.



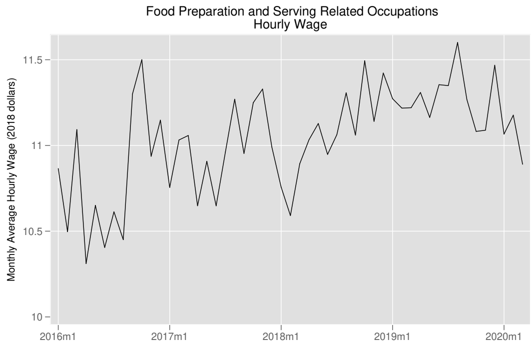
(a) Unemployment Rate.



(b) Labor Force Participation.



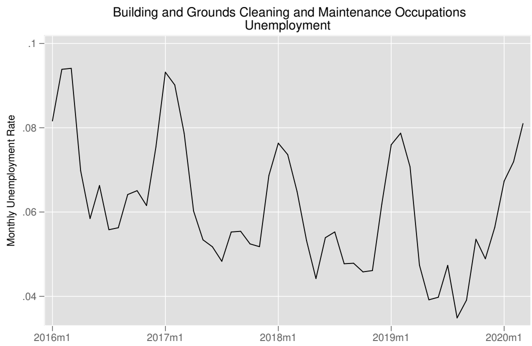
(c) Hours of Work.



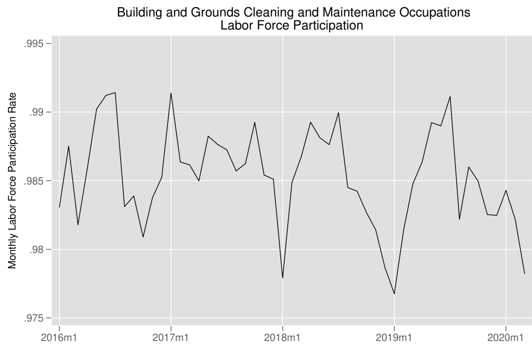
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

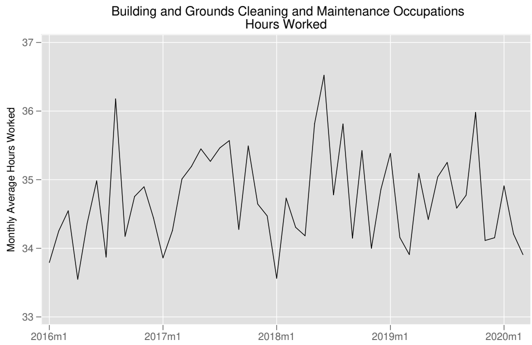
Figure A30: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Building and Grounds Cleaning and Maintenance Occupations.



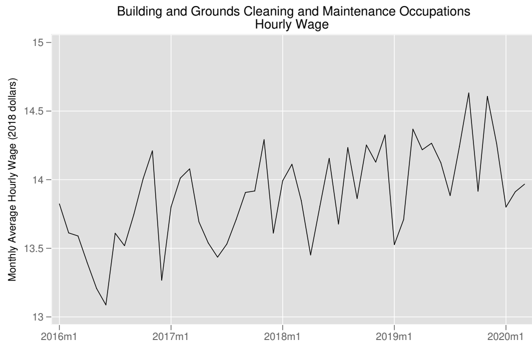
(a) Unemployment Rate.



(b) Labor Force Participation.



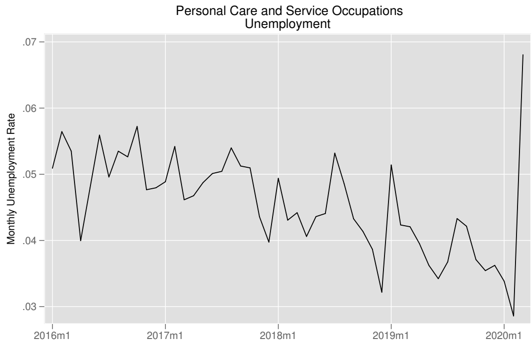
(c) Hours of Work.



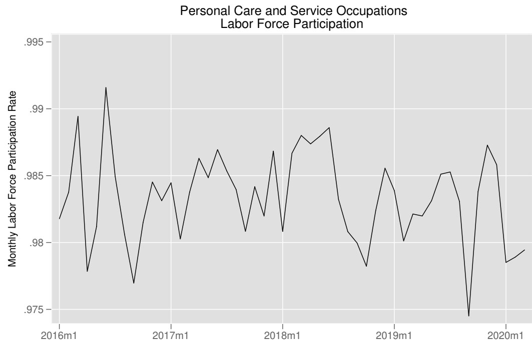
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

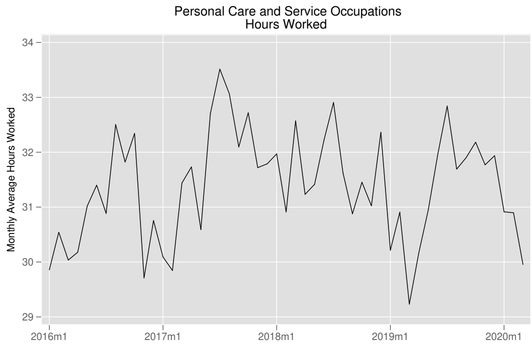
Figure A31: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Personal Care and Service Occupations.



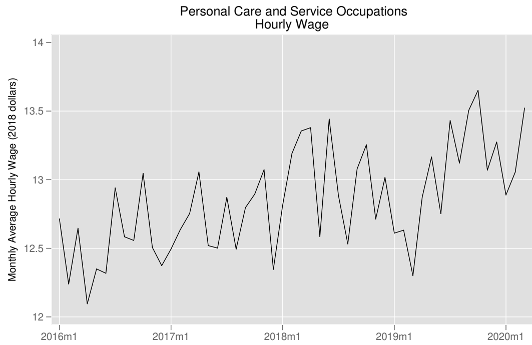
(a) Unemployment Rate.



(b) Labor Force Participation.



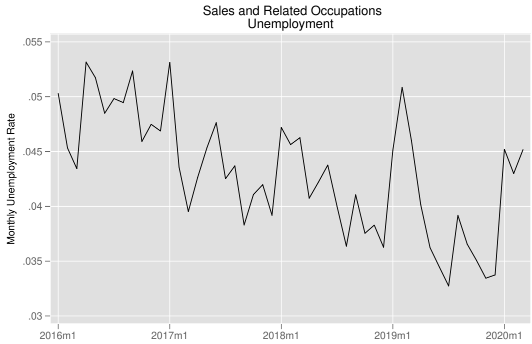
(c) Hours of Work.



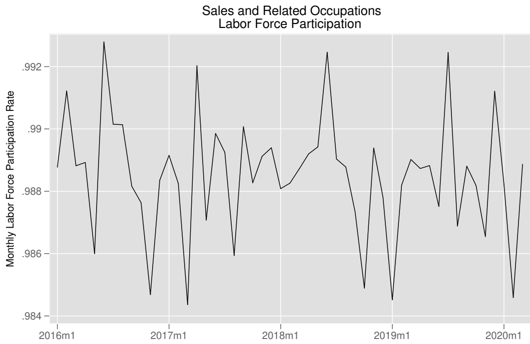
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

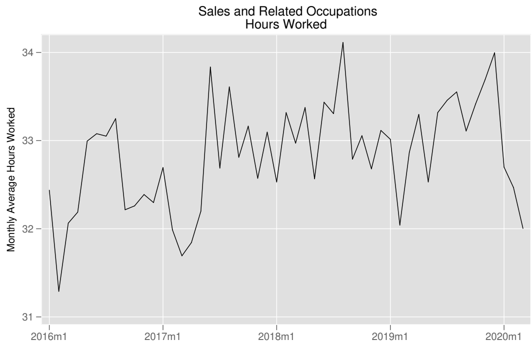
Figure A32: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Sales and Related Occupations.



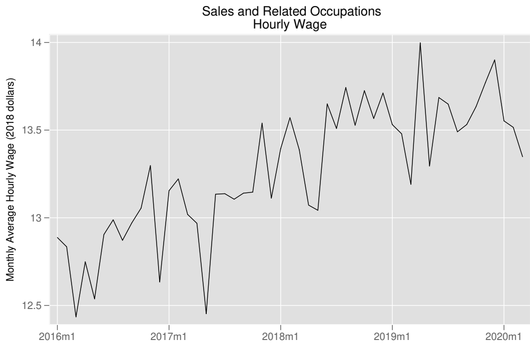
(a) Unemployment Rate.



(b) Labor Force Participation.



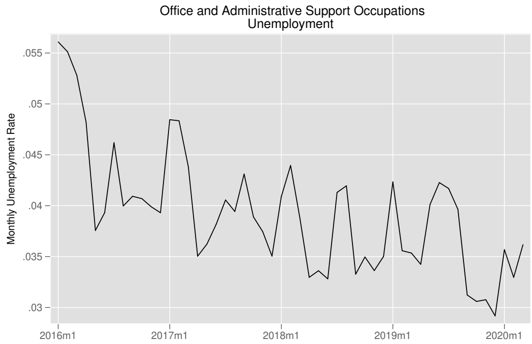
(c) Hours of Work.



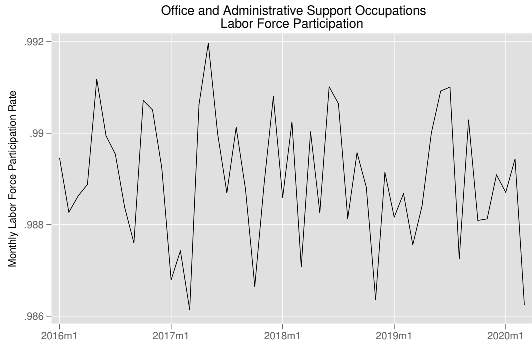
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

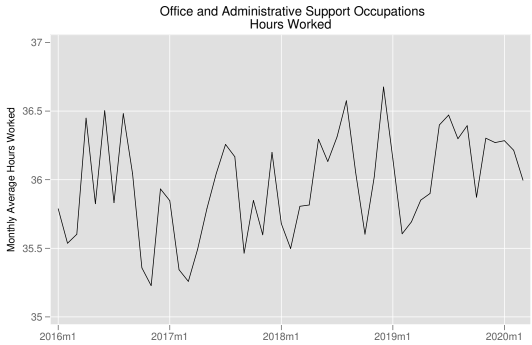
Figure A33: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages Office and Administrative Support Occupations.



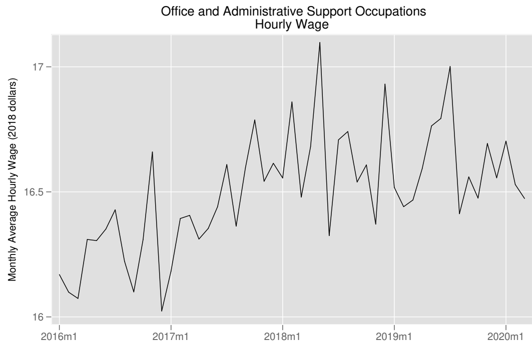
(a) Unemployment Rate.



(b) Labor Force Participation.



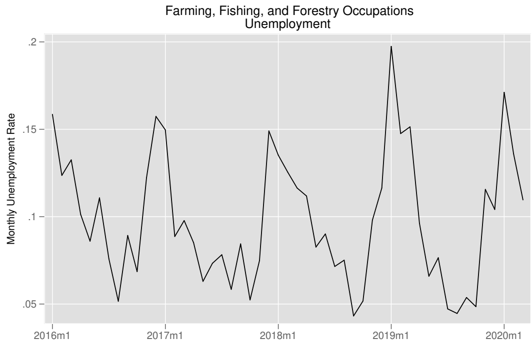
(c) Hours of Work.



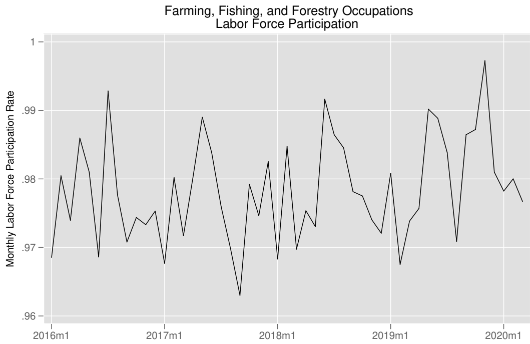
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

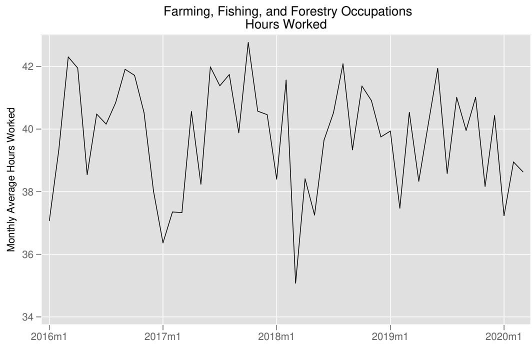
Figure A34: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Farming, Fishing, and Forestry Occupations.



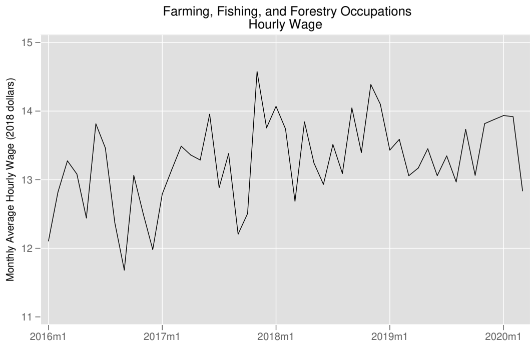
(a) Unemployment Rate.



(b) Labor Force Participation.



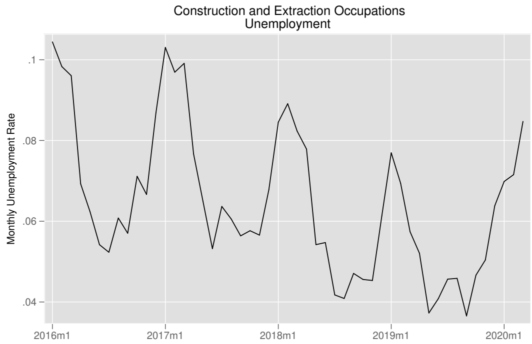
(c) Hours of Work.



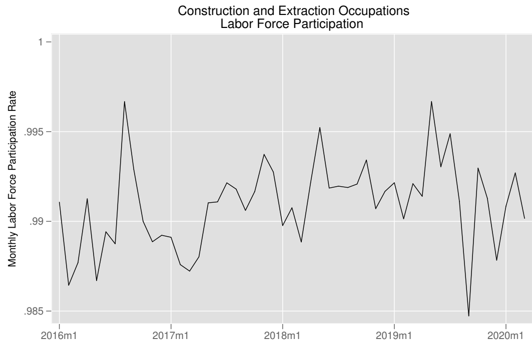
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

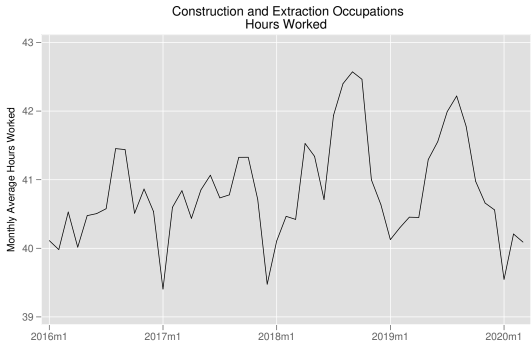
Figure A35: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Construction and Extraction Occupations.



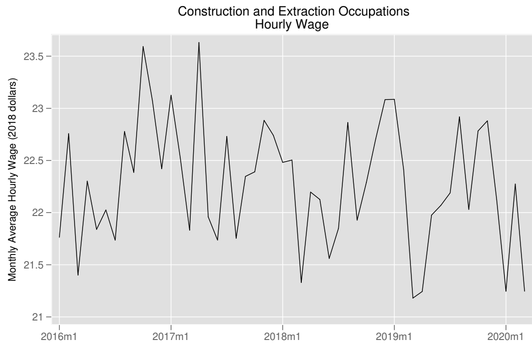
(a) Unemployment Rate.



(b) Labor Force Participation.



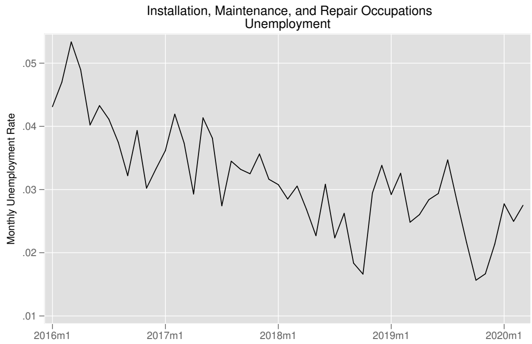
(c) Hours of Work.



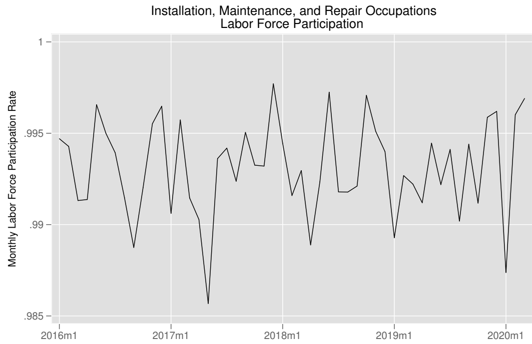
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

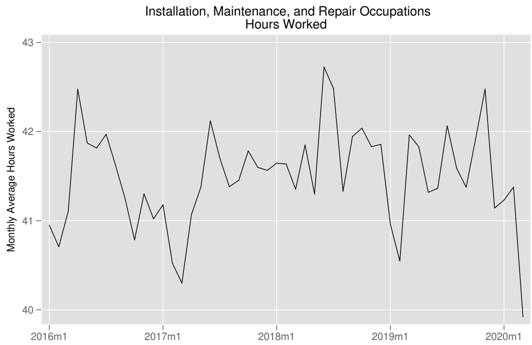
Figure A36: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Installation, Maintenance, and Repair Occupations.



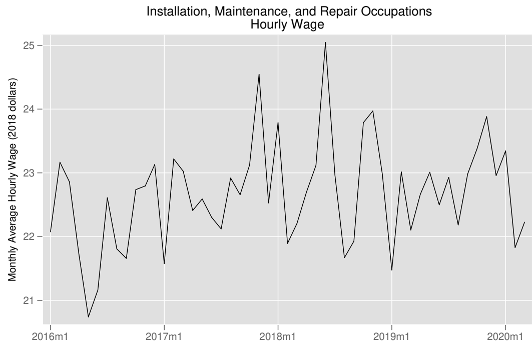
(a) Unemployment Rate.



(b) Labor Force Participation.



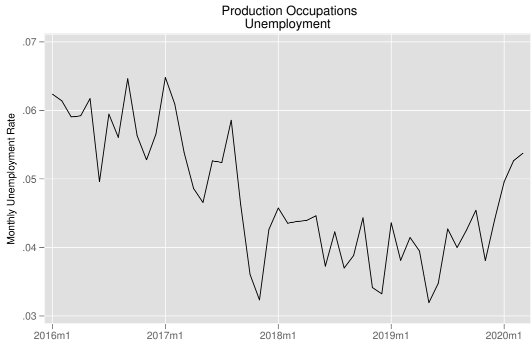
(c) Hours of Work.



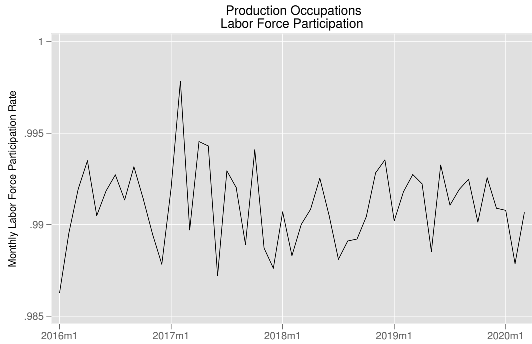
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

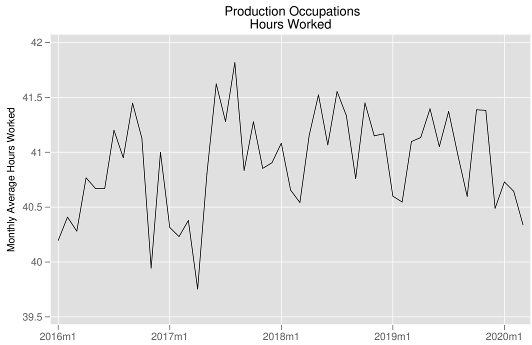
Figure A37: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Production Occupations.



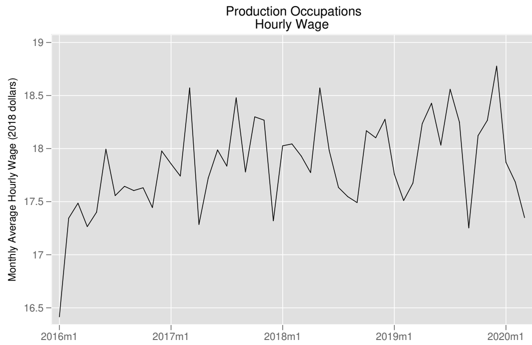
(a) Unemployment Rate.



(b) Labor Force Participation.



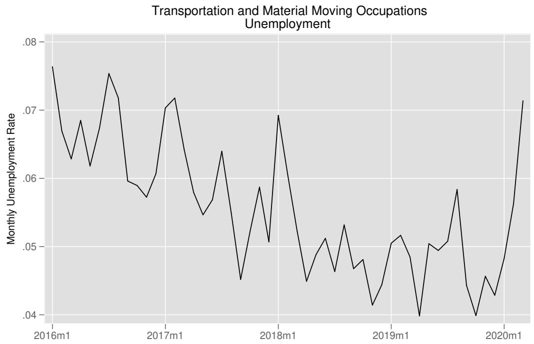
(c) Hours of Work.



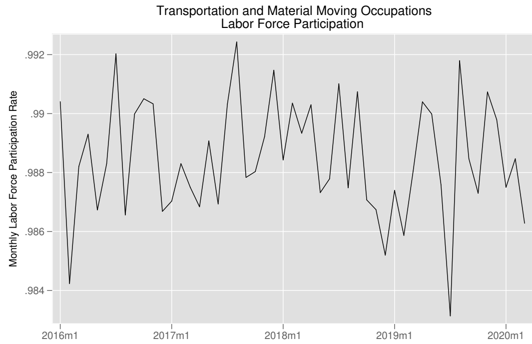
(d) Hourly Wages.

Notes: Authors' calculations. Data from the Current Population Survey. The time period is January 2016 to March 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.

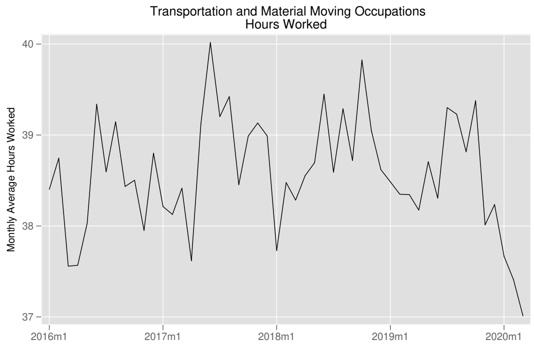
Figure A38: Unemployment Rate, Labor Force Participation, Hours of Work and Hourly Wages for Transportation and Material Moving Occupations.



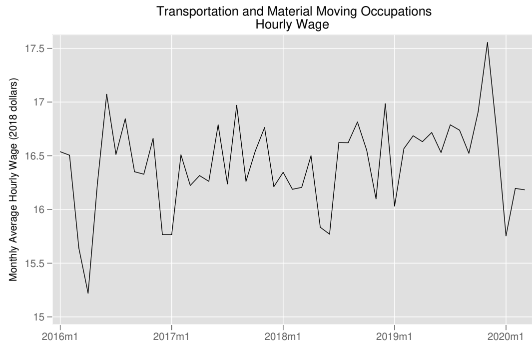
(a) Unemployment Rate.



(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 March 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.

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	

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: COVID-19 and Government Policies

State	**Date Stay Home Order** (1)	**Date School Closure** (2)
Alabama		16-Mar-2020 (Public)
Alaska		19-Mar-2020 (Both)
Arizona		16-Mar-2020 (Public)
Arkansas		17-Mar-2020 (Public)
California	19-Mar-2020	19-Mar-2020 (Both)
Colorado	26-Mar-2020	23-Mar-2020 (Both))
Connecticut	23-Mar-2020	17-Mar-2020 (Public)
Delaware		16-Mar-2020 (Both)
District of Columbia		16-Mar-2020 (Public)
Florida		16-Mar-2020 (Both)
Georgia		18-Mar-2020 (Public)
Idaho	25-Mar-2020	23-Mar-2020 (Public)
Illinois	21-Mar-2020	17-Mar-2020 (Both)
Indiana	24-Mar-2020	19-Mar-2020 (Both)
Iowa		n/a
Kansas		18-Mar-2020 (Both)
Kentucky		16-Mar-2020 (Both)
Louisiana	23-Mar-2020	16-Mar-2020 (Public)
Maine		n/a
Maryland		16-Mar-2020 (Both)
Massachusetts		17-Mar-2020 (Both)
Michigan	24-Mar-2020	16-Mar-2020 (Both)
Minnesota	27-Mar-2020	18-Mar-2020 (Public)
Mississippi	22-Mar-2020	20-Mar-2020 (Pubic)
Missouri		19-Mar-2020 (Both)
Montana	28-Mar-2020	16-Mar-2020 (Public)
Nebraska		23-Mar-2020 (Public)
Nevada		16-Mar-2020 (Both)
New Hampshire	27-Mar-2020	16-Mar-2020 (Public)
New Jersey	21-Mar-2020	18-Mar-2020 (Both)
New Mexico	24-Mar-2020	16-Mar-2020 (Public)
New York	22-Mar-2020	18-Mar-2020 (Public)
North Carolina	30-Mar-2020	16-Mar-2020 (Public)
North Dakota		16-Mar-2020 (Both)
Ohio	24-Mar-2020	17-Mar-2020 (Both)
Oklahoma	25-Mar-2020	17-Mar-2020 (Public)
Oregon	23-Mar-2020	16-Mar-2020 (Both)
Pennsylvania		16-Mar-2020 (Both)
Rhode Island		16-Mar-2020 (Public)
South Carolina		16-Mar-2020 (Public)
South Dakota		16-Mar-2020 (Public)
Tennessee		20-Mar-2020 (Public)
Texas		23-Mar-2020 (Both)
Utah		16-Mar-2020 (Public)
Vermont	25-Mar-2020	18-Mar-2020 (Both)
Virginia		16-Mar-2020 (Both)
Washington	23-Mar-2020	17-Mar-2020 (Both)
West Virginia	24-Mar-2020	16-Mar-2020 (Both)
Wisconsin	25-Mar-2020	18-Mar-2020 (Both)
Wyoming		20-Mar-2020 (Both)

Notes: Stay home order as of March 27, 2020. Includes orders that were announced, but not implemented, as of March 27, 2020. Massachusetts' governor announced an 'advisory' for residents to stay-home on March 24, 2020. School closure data as of March 27, 2020. 'Both' indicates that public and private schools are impacted. n/a indicates that closures are determined at district- or school-level.

Table A3: 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 A4: 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 A5: COVID-19 and Unemployment: Demographic Characteristics

	Unemployed			
	(1)	(2)	(3)	(4)
Post COVID	0.008	0.009	0.011	0.008
	(0.001)	(0.002)	(0.002)	(0.007)
Male	0.0014	0.0015	0.0015	0.0015
	(0.0009)	(0.0009)	(0.000946)	(0.0009)
Male × Post	0.0041			
	(0.0016)			
Age 16 to 34	0.017	0.017	0.017	0.017
	(0.001)	(0.001)	(0.001)	(0.001)
Age 35 to 54	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Age 16 to 34 × Post		0.0008		
		(0.0019)		
Age 35 to 54 × Post		0.0014		
		(0.0021)		
Married	-0.025	-0.025	-0.025	-0.025
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Married × Post			-0.0003	
			(0.0021)	
White	-0.017	-0.017	-0.017	-0.017
	(0.003)	(0.003)	(0.003)	(0.003)
Hispanic	-0.003	-0.003	-0.003	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Black	0.011	0.011	0.011	0.011
	(0.003)	(0.003)	(0.003)	(0.003)
White × Post				-0.0006
				(0.007)
Black × Post				-0.003
				(0.008)
Hispanic × Post				0.013
				(0.003)
Asian × Post				0.006
				(0.009)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	3,024,280	3,024,280	3,024,280	3,024,280

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 month of March 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–March 2020.

Table A6: COVID-19 and Labor Force Participation: Demographic Characteristics

	In Labor Force			
	(1)	(2)	(3)	(4)
Post COVID	-0.005	-0.003	-0.013	-0.012
	(0.004)	(0.004)	(0.004)	(0.011)
Male	0.116	0.116	0.116	0.116
	(0.006)	(0.006)	(0.006)	(0.006)
Male × Post	-0.006			
	(0.004)			
Age 16 to 34	0.192	0.192	0.192	0.192
	(0.010)	(0.010)	(0.010)	(0.010)
Age 35 to 54	0.257	0.257	0.256	0.257
	(0.004)	(0.004)	(0.004)	(0.004)
Age 16 to 34 × Post		-0.014		
		(0.006)		
Age 35 to 54 × Post		-0.001		
		(0.005)		
Married	0.039	0.039	0.039	0.039
	(0.002)	(0.002)	(0.002)	(0.002)
Married × Post			0.011	
			(0.006)	
White	0.013	0.013	0.013	0.013
	(0.005)	(0.005)	(0.005)	(0.005)
Hispanic	0.049	0.049	0.049	0.049
	(0.005)	(0.005)	(0.005)	(0.005)
Black	0.008	0.008	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.006)
White × Post				0.007
				(0.011)
Black × Post				-0.003
				(0.013)
Hispanic × Post				-0.004
				(0.006)
Asian × Post				0.004
				(0.017)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	4,310,529	4,310,529	4,310,529	4,310,529

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 month of March 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–March 2020.

Table A7: COVID-19 and Hourly Wages: Demographic Characteristics

	Hourly Wages			
	(1)	(2)	(3)	(4)
Post COVID	0.245	-0.238	0.120	-0.0748
	(0.245)	(0.261)	(0.220)	(0.638)
Male	2.701	2.695	2.695	2.695
	(0.0716)	(0.0734)	(0.0734)	(0.0735)
Male × Post	-0.342			
	(0.245)			
Age 16 to 34	-3.436	-3.444	-3.436	-3.436
	(0.0753)	(0.0752)	(0.0753)	(0.0752)
Age 35 to 54	0.152	0.147	0.152	0.152
	(0.0581)	(0.0589)	(0.0581)	(0.0581)
Age 16 to 34 × Post		0.459		
		(0.214)		
Age 35 to 54 × Post		0.290		
		(0.393)		
Married	1.952	1.952	1.954	1.952
	(0.0651)	(0.0651)	(0.0674)	(0.0650)
Married × Post			-0.0995	
			(0.248)	
White	0.636	0.636	0.636	0.635
	(0.164)	(0.164)	(0.164)	(0.159)
Hispanic	-1.321	-1.321	-1.321	-1.318
	(0.0905)	(0.0905)	(0.0905)	(0.0904)
Black	-1.136	-1.136	-1.136	-1.147
	(0.206)	(0.206)	(0.206)	(0.203)
White × Post				0.0837
				(0.639)
Black × Post				0.682
				(0.680)
Hispanic × Post				-0.176
				(0.253)
Asian × Post				0.662
				(0.957)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	386,312	386,312	386,312	386,312

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 month of March 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–March 2020.

Table A8: COVID-19 and Hours of Work: Demographic Characteristics

	Hours of Work			
	(1)	(2)	(3)	(4)
Post COVID	0.127	0.310	-0.218	-0.911
	(0.191)	(0.375)	(0.247)	(1.253)
Male	4.136	4.122	4.123	4.122
	(0.119)	(0.120)	(0.120)	(0.120)
Male × Post	-0.724			
	(0.257)			
Age 16 to 34	-1.383	-1.369	-1.383	-1.382
	(0.0962)	(0.0992)	(0.0960)	(0.0961)
Age 35 to 54	1.837	1.847	1.837	1.837
	(0.0990)	(0.0968)	(0.0989)	(0.0988)
Age 16 to 34 × Post		-0.761		
		(0.431)		
Age 35 to 54 × Post		-0.532		
		(0.420)		
Married	1.506	1.506	1.507	1.506
	(0.0694)	(0.0693)	(0.0690)	(0.0695)
Married × Post			-0.0307	
			(0.388)	
White	0.0181	0.0182	0.0181	0.000917
	(0.135)	(0.135)	(0.135)	(0.127)
Hispanic	1.393	1.394	1.394	1.400
	(0.122)	(0.122)	(0.122)	(0.124)
Black	0.935	0.935	0.935	0.928
	(0.159)	(0.159)	(0.159)	(0.156)
White × Post				0.917
				(1.296)
Black × Post				0.338
				(1.428)
Hispanic × Post				-0.340
				(0.317)
Asian × Post				0.177
				(1.446)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	360,212	360,212	360,212	360,212

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 month of March 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–March 2020.

Table A9: COVID-19 Cases and Unemployment: Demographic Characteristics

	Unemployed			
	(1)	(2)	(3)	(4)
Cumulative cases per 10,000 people	0.0200	0.0175	0.0172	0.0745
	(0.00744)	(0.00684)	(0.00996)	(0.0157)
Male	0.00146	0.00148	0.00148	0.00148
	(0.000947)	(0.000946)	(0.000946)	(0.000946)
Male × Cases	0.00747			
	(0.0114)			
Age 16 to 34	0.0169	0.0168	0.0169	0.0169
	(0.000974)	(0.000973)	(0.000974)	(0.000974)
Age 35 to 54	-0.0000769	-0.0000981	-0.0000771	-0.0000766
	(0.000712)	(0.000714)	(0.000712)	(0.000712)
Age 16 to 34 × Cases		0.00497		
		(0.00569)		
Age 35 to 54 × Cases		0.0108		
		(0.0125)		
Married	-0.0250	-0.0250	-0.0251	-0.0250
	(0.000605)	(0.000605)	(0.000605)	(0.000605)
Married × Cases			0.0121	
			(0.00959)	
White	-0.0172	-0.0172	-0.0172	-0.0171
	(0.00282)	(0.00282)	(0.00282)	(0.00283)
Hispanic	-0.00333	-0.00333	-0.00333	-0.00339
	(0.00112)	(0.00112)	(0.00112)	(0.00112)
Black	0.0109	0.0109	0.0109	0.0110
	(0.00284)	(0.00284)	(0.00284)	(0.00285)
White × Cases				-0.0567
				(0.0125)
Black × Cases				-0.0937
				(0.0181)
Hispanic × Cases				0.0283
				(0.0265)
Asian × Cases				-0.0292
				(0.0466)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	3024280	3024280	3024280	3024280

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. $CumulativeCasesper10,000$ is a dummy that is equal to one for the month of March 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–March 2020.

Table A10: COVID-19 Cases and Labor Force Participation: Demographic Characteristics

	In Labor Force			
	(1)	(2)	(3)	(4)
Cumulative cases per 10,000 people	-0.0252	-0.0101	-0.0451	-0.00277
	(0.0156)	(0.0146)	(0.0136)	(0.0650)
Male	0.116	0.116	0.116	0.116
	(0.00576)	(0.00574)	(0.00574)	(0.00574)
Male × Cases	-0.0215			
	(0.0210)			
Age 16 to 34	0.192	0.192	0.192	0.192
	(0.00960)	(0.00963)	(0.00960)	(0.00960)
Age 35 to 54	0.257	0.257	0.257	0.257
	(0.00381)	(0.00382)	(0.00381)	(0.00381)
Age 16 to 34 × Cases		-0.0600		
		(0.0329)		
Age 35 to 54 × Cases		-0.00881		
		(0.0172)		
Married	0.0390	0.0390	0.0390	0.0390
	(0.00216)	(0.00216)	(0.00216)	(0.00216)
Married × Cases			0.0174	
			(0.0182)	
White	0.0131	0.0131	0.0131	0.0131
	(0.00509)	(0.00509)	(0.00509)	(0.00513)
Hispanic	0.0493	0.0493	0.0493	0.0494
	(0.00525)	(0.00525)	(0.00525)	(0.00525)
Black	0.00768	0.00767	0.00767	0.00787
	(0.00610)	(0.00610)	(0.00610)	(0.00614)
White × Cases				-0.0234
				(0.0635)
Black × Cases			-0.102	
				(0.0782)
Hispanic × Cases				-0.0127
				(0.0302)
Asian × Cases				-0.0479
				(0.0950)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	4310529	4310529	4310529	4310529

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. $CumulativeCasesper10,000$ is a dummy that is equal to one for the month of March 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–March 2020.

Table A11: COVID-19 Cases and Hourly Wages: Demographic Characteristics

	Hourly Wages			
	(1)	(2)	(3)	(4)
Cumulative cases per 10,000 people	0.155	0.712	1.046	-1.598
	(1.116)	(0.894)	(0.608)	(4.593)
Male	2.671	2.672	2.672	2.672
	(0.0731)	(0.0742)	(0.0742)	(0.0742)
Male × Cases	0.802			
	(1.637)			
Age 16 to 34	-3.449	-3.449	-3.449	-3.449
	(0.0751)	(0.0746)	(0.0751)	(0.0751)
Age 35 to 54	0.158	0.158	0.158	0.158
	(0.0592)	(0.0590)	(0.0592)	(0.0593)
Age 16 to 34 × Cases		-0.285		
		(1.246)		
Age 35 to 54 × Cases		-0.0312		
		(1.323)		
Married	1.962	1.962	1.963	1.962
	(0.0636)	(0.0636)	(0.0639)	(0.0636)
Married × Cases			-0.972	
			(0.681)	
White	0.627	0.627	0.627	0.625
	(0.149)	(0.149)	(0.149)	(0.147)
Hispanic	-1.337	-1.337	-1.337	-1.338
	(0.0929)	(0.0929)	(0.0929)	(0.0924)
Black	-1.082	-1.082	-1.082	-1.086
	(0.192)	(0.192)	(0.192)	(0.192)
White × Cases				1.882
				(4.581)
Black × Cases				3.651
				(4.474)
Hispanic × Cases				0.490
				(1.081)
Asian × Cases				1.736
				(5.662)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	436263	436263	436263	436263

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 dummy that is equal to one for the month of March 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–March 2020.

Table A12: COVID-19 Cases and Hours of Work: Demographic Characteristics

	Hours of Work			
	(1)	(2)	(3)	(4)
Cumulative cases per 10,000 people	-1.677	0.433	0.794	-3.964
	(1.266)	(1.211)	(0.819)	(8.006)
Male	4.120	4.121	4.120	4.120
	(0.120)	(0.121)	(0.121)	(0.121)
Male × Cases	0.0302			
	(2.269)			
Age 16 to 34	-1.378	-1.377	-1.377	-1.378
	(0.0947)	(0.0952)	(0.0948)	(0.0947)
Age 35 to 54	1.842	1.850	1.842	1.842
	(0.0971)	(0.0963)	(0.0971)	(0.0970)
Age 16 to 34 × Cases		-0.483		
		(2.226)		
Age 35 to 54 × Cases		-5.032		
		(0.894)		
Married	1.504	1.504	1.513	1.505
	(0.0694)	(0.0694)	(0.0686)	(0.0694)
Married × Cases			-5.023	
			(1.098)	
White	0.0178	0.0181	0.0177	0.0151
	(0.135)	(0.135)	(0.135)	(0.131)
Hispanic	1.398	1.397	1.397	1.397
	(0.122)	(0.122)	(0.122)	(0.123)
Black	0.936	0.937	0.936	0.930
	(0.159)	(0.159)	(0.159)	(0.157)
White × Cases				2.055
				(8.277)
Black × Cases				4.508
				(8.215)
Hispanic × Cases				0.259
				(1.680)
Asian × Cases				0.779
				(9.144)
Individual Charact.	Yes	Yes	Yes	Yes
Interview Type FE	Yes	Yes	Yes	Yes
State, Month and Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Observations	360001	360001	360001	360001

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. $CumulativeCasesper10,000$ is a dummy that is equal to one for the month of March 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–March 2020.