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The intensity of COVID-19 Non-Pharmaceutical Interventions and labor market outcomes in the public sector

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Abstract

This paper examines whether the intensity of Non-Pharmaceutical Interventions (NPIs) during the COVID-19 pandemic has differentially impacted the public sector labor market outcomes. This extends the analysis of the already documented negative economic consequences from COVID-19 and their dissimilarities with a typical economic crisis. To capture the intensity of the NPIs, we build a novel index (COVINDEX) using daily information on NPIs merged with state level data on out of home mobility (Google data) to show that among individuals living in a typical state, the NPIs enforcement during the COVID-19 reduces the likelihood of being employed (at work) by 5% with respect to the pre-COVID period and the hours worked by 1.3% using data on labor market outcomes from the monthly Current Population Survey and difference-in-difference models. This is a sizable amount representing the sector with the higher job security during the pandemic. Public sector workers in a typical state are 4 percentage points more likely to be at work than salaried workers in the private sector and 7 percentage points more likely than self-employed workers (the worst so far). Our results are robust to endogeneity of the NPIs measures and present empirical evidence of heterogeneity in the response to the NPIs with those in the local employment being the hardest hit.

JEL: D1, J15, J16, J2, J23, J45

Keywords: COVID-19, coronavirus, public sector, remote work, essential worker, employment, hours worked

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1. Introduction

The COVID-19 pandemic declared on the 11th March 2020 by the World Health Organization (WHO) has shocked the world without precedent in recent history.¹ By the middle of August 2020, the Johns Hopkins Coronavirus Resource Center informed of almost 20 million total confirmed cases of what is known as the COVID-19 illness and more than 700,000 deaths.² We still do not know the end of the current pandemic crisis, but the 1918 flu pandemic scenario appears to be unlikely at least in the number of deaths (50 million (Correia et al., 2020)) and the age group affected (1918 flu: aged 20-40, COVID-19: aged +60 (Gagnon et al., 2013; Shanks, 2020)).³ The considerable differences in the epidemiological shock can generate dissimilar economic consequences of the COVID-19 in the long run from those of the 1918 flu.⁴ However, in the short term, the COVID-19 pandemic resembles other pandemics in the responses to contain and mitigate the spread of the virus using Non-Pharmaceutical Interventions (NPIs) such as school and non-essential business closures, public gathering bans, and isolation/quarantine (Markel et al., 2007). NPIs has been found that constrain social interactions to save lives (Bootsma & Ferguson, 2007; Hatchett et al., 2007) at the expense of a reduction in economic activity through reductions in the demand of goods and services and disruptions in the supply chains and production (Correia et al., 2020). Is this really happening in the public sector during the COVID-19 pandemic? Indeed, the answer is: we do not know. To our knowledge, there is no prior research on this issue. In this work, we explore how NPIs affect public employment outcomes and whether

¹ It was at the end of December 2019 and early January 2020, when the World Health Organization China Country Office reported the existence of pneumonia cases of an unknown novel coronavirus in the city of Wuhan (Hubei, China), re-called as SARS-CoV-2 (Brodeur et al., 2020). See also a worldwide review of coronavirus events the WHO website: <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen> (Updated August 2020)

² The United States (US) at the top of the hardest hit countries (with more than 5 million confirmed cases and 163,000 deaths, Johns Hopkins Coronavirus Resource Center (Updated August 2020).

³ The 50 million deaths represent the 2% of the total population in the World which is the equivalent to 150 million using the current population with around 675,000 in the U.S. (Barro et al., 2020; Correia et al., 2020).

⁴ Barro et al. (2020) estimated that the flu death rate of 2% of the total population in 1918-1920 could have reduced real per capita GDP and private consumption in the typical country by 6 and 8 percent, respectively. This could be considered as the plausible worst-scenario to the today's pandemic.

there are differences with the private sector.

There is a growing body of literature examining the short-run economic consequences of COVID-19 and NPIs (see, for an extensive review, Brodeur et al., 2020) mainly concentrated on employment outcomes (Baek et al., 2020; Béland et al., 2020; Cowan, 2020; Forsythe et al., 2020; Gupta, Montenovov, et al., 2020). For the U.S., empirical findings point to stay-at-home orders (which are a type of NPIs) as possible factor explaining 60% of the decline in the employment rate from January 2020 to April 2020, the rest (40%) should be due to the nationwide shock caused by the COVID-19 (Gupta, Montenovov, et al., 2020). The decline in the employment was not limited to the private sector in the early stages of the pandemic crisis. During this crisis almost no-one can be considered safe. In the U.S., total nonfarm payroll employment fell by 20.5 million in April, after declining by 881,000 in March. Part of those job losses are government employment reductions (980,000 in April including local, state and federal employment according to the Bureau of Labor Statistics (BLS April 2020)).⁵ In June 2020, government employment was still 1.5 million below its February level representing a decline of 7% (BLS June 2020).⁶ While there were substantial job gains in several sectors (retail trade, education and health services, other services, manufacturing, and professional and business services), this was not observed in the public sector (BLS June 2020). Is this pattern of early declines and jobs and late recovery what we would expect comparing this crisis with other economic recession?

During a traditional economic crisis, public sector employment is expected to be less sensitive to economic recession than private sector employment following different paths in the magnitude and in the timing of declines and recovery, being normally less negatively affected at the beginning of the recessions (Fontaine et al., 2020; Kopelman & Rosen, 2016; Laird, 2017). For example, during the last Great Recession in the U.S., government employment grew during the first months of the recession of 2008, this behavior is also observed in the crisis of 1990–91 and 2001 (Fontaine et al., 2020; Goodman & Mance, 2011; Hatch, 2004). Government

⁵ https://www.bls.gov/news.release/archives/empsit_05082020.pdf (Updated July 2020)

⁶ https://www.bls.gov/news.release/archives/empsit_07022020.pdf (Updated July 2020)

employment is driven by other objectives including: budgetary targets, stabilization policies and/or electoral objectives (Fontaine et al., 2020). The public sector has more difficulties in order to reduce public expenditure by, for example, cutting jobs in the face of an income shortfall (Craig & Hoang, 2011). This is especially problematic in the U.S. for state and local governments, which account for the 90% of public jobs in 2018 (BLS 2019), since they have less flexibility to run deficits and they normally adjust their budget on an annual basis after September because of the budget process established in the budget calendar (Goodman & Mance, 2011).⁷ Additionally, since governments focus on public good problems whose demand normally increases during economic downturns, they design policies to respond to this problem without necessarily altering other categories of expenditure in the short run (Craig & Hoang, 2011). In the current pandemic crisis, apparently, the public and private sector have followed similar trajectories in the U.S. We argue here that NPIs are playing a role in the public sector response to the public health crisis in a different way than what can be expected from business cycle fluctuations.

NPIs such as school closures directly damage the public sector employment because of the employment composition of the public sector. This is especially dramatic in local and state government in the U.S. since more than half of state and local workers are in education-related jobs (Hinkley, 2020). Those closures are suggested to indirectly affect the employment of health care workers since it is calculated that 15% of those workers are in need of childcare during school closures in the U.S. (Bayham & Fenichel, 2020). Studies using real-time data from marketing surveys present evidence that the additional childcare burden can be penalizing households with children, with women more affected than men without paying attention in the private/public sector differences. This is of interest in the public sector employment, given that women are over-represented by 3-4 more percentage points -especially black women- in the U.S. public sector (Laird, 2017). Adams-Prassl et al. (2020) show that in April, women were 8 percentage points more likely to lose their jobs. This can be explained in part because women are doing the greater

⁷<https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm> (Updated July 2020)

share of childcare during the pandemic (Biroli et al., 2020; Del Boca et al., 2020; Farré et al., 2020; Sevilla & Smith, 2020). In this pandemic, there have not only been school closures, the closure of non-essential public service and the lockdowns may also negatively affect the level of employment and/or the hours of work of those that cannot do their work task remotely (Gupta, Montenov, et al., 2020). Only positively affected can be the level of employment of those in the front line during the pandemic but even for those public services that have seen an increase in the demand, the NPIs should reduce the necessities of new health care workers and/or more hours of work by alleviating the impact of the pandemic. To make all this possible in a short space of time, unlike what happens in economic crisis, the public sector in the U.S. need the declaration of a state of emergency, which has been crucial to give access to additional resources and to ease the employment transitions by relaxing laws and regulations at the local, state and federal level.⁸ Our work focuses on testing whether those U.S. states with more intense NPIs, which theoretically appear to affect negatively the public sector employment outcomes, are those losing more public jobs and/or reducing more hours of paid jobs.

We exploit the large differences in how states in U.S. have tried to contain the spread of the COVID-19 virus. The U.S. is an interesting case study because, unlike other countries, each state in the United States is acting independently. Although the CDC (Centers for Disease Control and Prevention) has made some recommendations, states are free to take their own decisions.⁹ It is also an attractive framework to study the response of the public sector employment. In other countries, extremely hit by the pandemic such as Spain, there have been no reductions in the public employment during the earliest stages of the pandemic with the exception of limiting freeze hiring during the hard period of the lockdown. U.S. public sector accounts for 1 to 7 workers in the U.S. (13.9% of the 161 millions of U.S. workers) in 2018 which is a sizable proportion in

⁸ Emergency declaration includes State of Emergency, Public Health Emergency, and Public Health Disaster declarations. These actions allow flexibility regarding a variety of state laws and regulations; these can vary greatly to include waiver of procurement rules, easing of licensing requirements, exceptions to transportation rules, even suspension of school attendance laws, and many other changes meant to facilitate a more efficient response.

⁹ In some cases, there are also variations within the state on how counties reacted that we check in the robustness analysis.

comparison with other sectors and countries (18% for OECD countries varying from 30% in Norway to 6% in Japan in 2015 (OECD, 2017)).¹⁰ In our analysis, we use individual level data on employment outcomes and socio-demographic characteristics from the monthly Current Population Survey, spanning through May 2020. We merge this information with a novel index (COVINDEX) that captures the timing and intensity of the NPIs by state and month. Using the assembled data, we estimate a difference-in-difference model aimed at gauging how NPIs affect labor supply in the public sector and comparing it with the private sector for various population subgroups (heterogeneity analysis). The two employment outcomes of interest are individuals' employment propensity, and the actual number of hours worked for those who report working.

Measuring the NPIs in the U.S. is not straightforward. To gauge it, we use a weighted index, COVINDEX. We collect daily information on the announcement of five NPIs and their expiration at the state level, if any (state of emergency, school closures, partial business closures, stay-at-home orders, and non-essential business closures). We combine this with the out of home mobility data provided by Google (Google LLC, 2020). We capture, in an easy way, the intensity of the NPIs lessen the difficulties in measuring one by one the diverse regulations and their timing across U.S. states. Prior literature on the impact of NPIs on employment only considers an indicator variable, which is not able to capture the differences across states in the NPIs enforcement, mainly focusing only on stay-at-home orders and/or business closures (Béland et al., 2020; Gupta, Montenovio, et al., 2020). We add to this line of research by extending the number of NPIs and better measuring the enforcement of the NPIs in an easy way with one index for state and month.

The adoption of NPIs and the level of effectiveness and compliance, could be correlated to the incidence of the COVID-19 in a way that may bias the regression estimates upwards. Also, the differences in the NPIs introduced in the states that can be related with their democratic or

¹⁰The last annual data available in the BLS see: <https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm> (Updated July 2020). This is not a minor sector in terms of employment in comparison to other sectors, for example: the number of workers in retail trade are only the 10.2% of the total workers or the 13% in professional and business services.

republican control (Adolph et al., 2020; Allcott et al., 2020) can generate endogeneity concerns that has been mitigated in this study by using event studies. To provide additional evidence on the validity of our findings, we present an extensive number of robustness checks in the Appendix.

The paper is organized as follows. Section 2 describes the data used in the analysis, and Section 3 presents the empirical specification, including the description of the COVINDEX. Section 4 discusses the main findings, as well as identification and robustness checks. Section 5 presents some heterogeneity analysis and Section 6 concludes.

2. Data

We use the Basic Monthly Current Population Survey (CPS) from the Integrated Public Use Micro Samples (IPUMS (Flood et al., 2020)). This is a household-level monthly survey of approximately 50,000-60,000 households and includes information about everyone in the surveyed households. The CPS is the main source of labor force statistics for the population in the U.S. sponsored by the U.S. Census Bureau and the BLS. Several papers examine the short-term impact of COVID-19 on U.S. employment with the CPS (Béland et al., 2020; Gupta, Montenegro, et al., 2020), because it provides enough observations to obtain reliable estimations. COVID-19 impacted the data collection with the response rate dropping by 10 (March), 13 (April), and 15 (May) percentage points in 2020 with respect to the same months of 2019.¹¹ The concern on possible sampling error problems is mitigated by the BLS, that agency claims that with this dataset is “still able to obtain estimates that met [their] standards for accuracy and reliability”.¹²

For our main sample, we use data spanning from January 2019 through May 2020. This time period allows us to perform event studies assessing the exogeneity of the COVINDEX with respect to public employment outcomes, as well as to control for the seasonality of the data by

¹¹ <https://cps.ipums.org/cps/covid19.shtml> (Updated July 2020)

¹² The data collection method was also affected since all interviews had to be conducted by telephone. Our results prove robust to controlling for whether the interview was done in-person or telephone (see Appendix B Table B1). The BLS is releasing supplementary information about the impact of the COVID-19 pandemic. See Employment Situation Summary BLS of March, April, and May <https://www.bls.gov/bls/news-release/empst.htm>. (Updated July 2020):

including month fixed effects. Our main sample is restricted to working-age (18-64), non-institutionalized civilians whose current or most recent job is in the public sector according to the type of ownership of the employing organization as in Laird (2017).¹³¹⁴ It is excluded those in armed forces since CPS does not include military personnel. Our main sample consists of 129,502 individuals, representing the 14% of salaried private/public and self-employed workers during the January 2019 through May 2020 period examined here.

2.1 Labor Market Outcomes

We pay attention on two labor market outcomes in the main analysis. The respondent's employment status as captured by the variable *employed*, which takes the value 1 if the respondent reported being *at work* with a main job in the public sector and 0 if he/she has a job but *did not work last week* and if he/she is *unemployed or not in the labor force* with their more recent main job being in the public sector.¹⁵ We focus on those employees *at work* to mitigate a possible non-sampling error problem which can bias upward the possible negative impact of NPIs on employment propensity generated by the misclassification of some individuals in the category furlough absent from work. BLS analysis of the CPS data in March, April and May suggests that this group included workers affected by the pandemic response who should have been classified as unemployed on temporary layoff.¹⁶

¹³ Our sample does not include minors since the Fair Labor Standards Act (FLSA) sets specific wage, hours worked, and safety requirements for minors (individuals under age 18), and this can vary at the state level. We probe the robustness of our findings to this sample selection including individuals aged 16 to 64 in Table B2 in the Appendix B.

¹⁴ According to the technical documentation of the CPS, current job is the job held in the reference week (the week before the survey) for the employees and self-employed workers. Workers with multiple sources of employment were classified according to the job in which they worked the most hours. Respondents who were not employed during the previous week reported the most recent job. The unemployed are classified according to their latest full-time job lasting two or more weeks or by the job (either full-time or part-time). The most recent job is also reported by persons not in the labor force who are in the fourth and eighth months in sample and who have worked in the last five years.

¹⁵ Main job is the job at which the person usually works the most hours. If a person usually works the same number of hours at two jobs, the "main" job is the job at which the person has been employed the longest.

¹⁶ For those who did not work at all during the survey reference week, people who indicated they were under quarantine or self-isolating due to health concerns should be classified under "own illness, injury, or medical problem." People who were not ill or quarantined but said that they did not work last week "because of the coronavirus" should be entered as "on layoff (temporary or indefinite)." However, a significant part of them were included in the category *did not work last week* because "other reasons". For example, in April, if workers who were recorded as employed but absent from work due to "other reasons" had been

For those respondents being at work during the last week, we examine at the intensive margin the number of actual hours worked in the public sector when this is their main job.¹⁷ Although there could be individuals working in secondary jobs in the public sector, we have to limit our analysis to the main job since the use of the actual hours worked in all jobs may generate a measurement error problem. The CPS only provides information on the class of worker by the type of ownership of the employing organization (salaried public, salaried private or self-employed worker) for the main job.¹⁸ The hours worked are in logarithm in the main analysis.

For the labor outcome variables considered here, respondents are usually asked to report about them by the CPS for the 7-day calendar week (Sunday–Saturday) that includes the 12th of the month (or the 5th in the case of December).¹⁹ Considering this, the March CPS refers to early March prior to the onset of the pandemic in most U.S. states and so to the application of hard NPIs. As can be seen in Table 1, which displays the composition of the labor force by sector for pre-COVID (January 2019 to February 2020) and post-COVID periods (separately for March, April, and May), the disparities in labor outcomes are much more evident in April (the percentage of individuals being at work is significantly reduced by 8.6% in the public sector and the work hours by 1.5%), there is not much of a change in March 2020 in the employment outcomes.²⁰ In any case, the drop observed here is sizable in comparison to the percentage of people employed in the public sector during the period 2003-2013 which is above the 92%, even including the last Great Recession (Laird, 2017). May shows a significant recovery of 4 percentage points respect to April in the percentage of individuals at work whereas the hours worked change slightly, which can be related to the reopening process. This pattern is maintained in all the worker categories

classified as unemployed on temporary layoff, the overall unemployment rate would have been almost 5 percentage points higher than reported. See Employment Situation Summary BLS of March, April, and May.

¹⁷ We trim the extremes without those below the 1st percentile (working less than 5 hours in the public service) and above the 99th percentile (working more than 70 hours per week) as in (Béland et al., 2020). Our findings are maintained without its exclusion, see table B3 in the Appendix B.

¹⁸ We have showed the robustness of our findings by considering hours worked in all jobs and also by limiting the sample to individuals that do not spend time in second jobs, see table B4 in the Appendix B.

¹⁹ <https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/collecting-data.html>

²⁰ Table A1 in the Appendix A shows when the differences are statistically significant.

(salaried public, salaried private, or self-employed worker). The main difference is observed in the category having a job but absent, which significantly increased in April for self-employed workers. This is also due, in part, for the way in which data is processed by the CPS. The “on layoff (temporary or indefinite)” response option is not available for business owners who have no other job, so they are included in the category furlough absent from work for “other reasons” when they do not have a job. Because some authors suggest the importance of learning about those individuals having a job but being absent (Montenovo et al., 2020), we have incorporated this to the secondary analysis when separating the sample by class of worker category. We define a variable *did not work last week* for whether an individual has a job but did not work last week. In any case, this should be taken with caution because of the aforementioned misclassification of some workers in the category having a job but being absent rather than unemployed.

2.2 The Intensity of NPIs

In this work, we explore which part of the changes in the labor outcomes in the public sector can be explained by the intensity of NPIs. There are variations on the space, scale, and timing of the NPIs as well as on their effectiveness and compliance across U.S. states. In any state, individuals may be exposed to a multiplicity of NPIs which make no straightforward analysis of each of the NPIs individually (Gupta, Montenovo, et al., 2020). For this reason, we build a weighted index to gauge the intensity of the NPIs using daily information on the announcements of five NPIs, and their expiration, if any (state of emergency, school closures, partial business closures, stay-at-home orders, and non-essential business closures), and daily real-time data on the mobility of the population.²¹ We start by calculating the number of days in which the NPIs has been applied

²¹ Emergency declarations include state of emergency, public health emergency, and public health disaster declarations. Partial business closures incorporate partial closures without specifying the closures of non-essential business such as restriction or limitation of restaurants, casinos, gyms, fitness centers and entertainment venues among others. Non-essential business closures are mandates to close all non-essential businesses. Stay-at-home orders refer to mandates for individuals to stay at home for all non-essential activities. These definitions come from (Fullman et al., 2020). We combine several sources of information (for the NPIs announcements: Fullman et al., (2020), Education Week, National Governors Association (NGA); for the reopenings: NGA; New York Times, and Johns Hopkins Coronavirus Resource Center) see Table E2 in the Data Appendix for a detailed information. As robustness, we have calculated the index at the county level with the same NPIs (National Association of Counties (NACo), Education Week, Fullman et al., (2020), and NGA) with the dates of the reopening being established at the state level. See Table B5 in the Appendix B which maintains our findings. It should be noted that in the case of county data we have

in each month. This daily information is weighted by the estimated average impact of each NPIs on the mobility using data from the COVID-19 Google Mobility Reports (Google LLC, 2020).

Real-time data on mobility have been used in the last months to learn about the COVID-19 pandemic (Chetty et al., 2020; Gupta, Nguyen, et al., 2020; Painter & Qiu, 2020). The effectiveness of NPIs to contain the spread of the virus by reducing social interactions is strongly supported in this pandemic (Amuedo-Dorantes et al., 2020; Badr et al., 2020; Dave et al., 2020; Prem et al., 2020) with a 9% reduction of daily case growth rate after the implementation of stay-at-home orders and restaurant closures in the US (Courtemanche et al., 2020). Although much of the literature concentrates on the impact of stay-at-home orders on mobility, there is some evidence on the early impact of several NPIs finding that the estimated average effect of state-of-emergency declarations resulted in approximately a 10% reduction in the mobility away from places of residence, each of the additional partial closures resulted in an additional 25% reduction, and the stay-at-home orders add a 29% drop until the 29th March (Wellenius et al., 2020). We extend this analysis by separately examining this issue for each state as follows:

$$Mobility_{ist} = \sum_{i=1}^{MC} \sum_{j=1}^N (\beta_{ijs} NPI_{jst}) \theta_i + \delta_m + \theta_i + \varepsilon_{ist} \quad (1)$$

where $Mobility_{ist}$ measures relative changes (in percentage) in the total number of visitors of the category of mobility i ($i=1, \dots, MC$ ($MC=5$, five categories of mobility)) in state s in day t with respect to the baseline, which is the median value, for the corresponding day of the week, during the 5-week period from January 3–February 6, 2020.²² We considered the five out of place of residence categories of mobility provided in the Google Mobility Reports (retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces) for the period 15 February to 12 May 2020.²³ NPI_{jst} is a dummy variable that takes the value 1 since state s declares a NPI j in

limited the sample to counties with at least 200 observations for all mobility categories in order to obtain reliable estimations. This reduces the number of counties with available data on mobility from 2,829 to 2,749.

²² This data is obtained from <https://www.google.com/covid19/mobility/>

²³ Retail and recreation covers visits to restaurants, cafes, shopping centers, theme parks, museums, libraries, movie theaters, and similar locations. Grocery and pharmacy covers markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Parks covers public beaches, marinas, dog parks, plazas, and other public spaces. Transit stations covers subway stops and bus and train stations.

day t until its expiration date, if any, with j varying from 1 to N , being N the maximum number of NPIs applied in state s .²⁴ θ_i is a set of mobility fixed effect which are meant to capture fixed differences in the level of outcomes across categories of mobility that are stable over the study period. δ_m is a set of month fixed effects, which capture trends in the outcome that are common across all categories of mobility such as seasonality. ε_{ist} is the error term. We run this regression for the 50 states plus District of Columbia. Our estimates are based on a panel of categories of mobility by state, which allows us to have enough observations (440 for each state) to run reliable estimations. β_{ijs} are the coefficients of interest. Those coefficients capture the average effect of each NPI on the relative change of visitors for each category of mobility. Those β_{ijs} which are statistically significant at least at the 10% level are used to calculate the COVINDEX. These estimations are based on the idea that human mobility patterns show a high degree of temporal and spatial regularity with the pandemic prevention/containment being able to break the inherent mobility patterns (González et al., 2008). In any case, our estimates can be considered as a lower bound of the average effect of the NPIs on mobility since partly could be explained by voluntary changes in behavior because of the evolution of the pandemic (Gupta, Nguyen, et al., 2020).²⁵

An additional caveat of the dataset is that reports use data from individuals who have opted-in to Location History for their Google Account, so the data represents a sample of their

Workplaces covers places of work. Residential category is not included in the analysis because it differs to the rest of categories in the unit of measure. Residential category shows a change in the duration, see <https://support.google.com/covid19-mobility/answer/9825414?hl=en>

²⁴ We have considered announcement dates since the exact date of the announcement is supposed to be exogenous although there are no significant differences with the date of the implementation, only a gap between 1 and 3 days (Gupta, Nguyen, et al., 2020). We revisit this issue below.

²⁵ Some works suggest that all 50 states (plus D.C.) display similar quantitative pattern previous to the declaration of stay-at-home orders (Farboodi et al., 2020; Gupta, Nguyen, et al., 2020). They point to voluntary changes in the mobility patterns. We recognize that voluntary changes in the mobility could partly explain the decrease in the mobility but it could be more plausible that at the early stages of the pandemic (second-third week of March) prior to the declaration of the stay-at-home orders, the state-wide implementation of state of emergency, school closures, and partial business closures could drive that similar pattern in the mobility. We have also introduced a sub-index in the main regression to control for the possible impact of the evolution of the pandemic by using the daily information on the announcement of first COVID-19 death in each state and results are robust to the inclusion of this control. See Appendix B Table B6.

users, not the whole population.²⁶ Additionally, it may not be able to account for people who spend time near a location. To lessen possible sampling error problems, they only show reports on regions from which they obtain statistically significant data.²⁷

Following the recent literature that developed indices weighted by the exposed population on policy enforcement (Amuedo-Dorantes et al., 2018; Amuedo-Dorantes & Lopez, 2015), we calculate the COVINDEX by considering the timing of the NPIs weighted by the average estimated effect of the NPIs on the relative change in the total number of visitors to five set of locations. The COVINDEX of state s in a given month m is:

$$COVINDEX_{sm}^{2020} = \sum_{i \in MC}^{MC} \sum_{j \in N}^N \frac{1}{D} \sum_{d=1}^D \mathbf{1}(NPI_{ijd}) W_{ij} \quad (2)$$

with MC being the categories of mobility. W_{ij} equals $\hat{\beta}_{ijs}$ when the estimated effect of the NPI j on the category of mobility i is statistically significant at least at the 10% level, and 0 otherwise.²⁸ This is measured as a relative change of the total number of visitors to the five set of locations, which can be interpreted as the portion of population exposed to the NPI as in the case of policy enforcement indices. NPI_{ijd} is an indicator function that takes value one since NPI j is implemented in day d of month m until its expiration, if any, whereas D is the total number of days in month m . To make sure the NPIs refers to the same period for which the CPS was collected, each month expands from the 13th of the month to the 12th of the next month. To easily interpret the estimated coefficients in the ulterior regressions, we divide this index by 100.

The COVINDEX is by definition bounded below to a value of -5 when as a consequence of the NPIs there are no visitors to the five set of locations in state s (maximum enforcement) during the entire month m . When the COVINDEX takes the value of 0 (no enforcement), this means that NPIs are not implemented or, if declared, there is no statistically significant effect of

²⁶ According to the Kantar Worldpanel ComTech, U.S. sales of Android, the Google system for mobile devices, exceed the 50 % of the total sales in U.S. This should mitigate concerns on the representativeness of the data used. See <https://www.kantarworldpanel.com/global/smartphone-os-market-share/> (Updated July 2020).

²⁷ There are 3 days without data on the category parks in Delaware and 1 in Idaho.

²⁸ In an unlikely scenario of no physical interactions caused by NPIs in a specific location $i \sum_{j \in N} W_{ij}$ should reach the value -100.

the NPIs on the categories of mobility (no change in the social interactions). Negative values should be interpreted as a reduction of social distancing. The more intense (effective) the NPIs in reducing social interactions, the closer the value of the COVINDEXT to -5. The COVINDEXT can take positive values when at least one of the NPIs encourages social interaction (this happens when the total number of visitors exceed that of the baseline period as a consequence of the NPI implementation) and none of the rest NPIs has statistically significant effects or, if significant, cannot compensate the estimated positive effect.²⁹

As shown in Table 1, the COVINDEXT over the post-COVID period (March, April, and May 2020) averaged -1.02 and fluctuated between 0.05 and -2.6.³⁰ To provide a sense of the evolution of the NPIs enforcement during the post-COVID period, Panels A-C in Figure 1 shows the evolution of COVINDEXT over that time. Lighter colors correspond to lower levels of NPIs enforcement (higher levels of the COVINDEXT means low effectiveness of the NPIs on reducing social interactions) in each state and month. Enforcement levels in the U.S. has multiplied by a hundred during this period. In the first month of our post-COVID sample, 17 states had a COVINDEXT equal to zero (i.e., no enforcement), among the rest 23 have a COVINDEXT lower than zero (reducing social interactions) and (11) had COVINDEXT higher than zero (encourage social interactions). By April and May, all states have NPIs enforcement index lower than 0. In addition, the COVINDEXT for most states decrease over time (the more intensity the lowest the COVINDEXT). It decreases for all states from March to April and for 36 states from April to May.³¹ Although some states started with relative high intense NPIs in comparison with the rest of the states, the states with higher intensity of the NPIs (lowest COVINDEXT) are mainly

²⁹ This only happens in March when, for instance, the emergency declarations appear to increase and school closures appear to increase the visitors to parks and groceries. Since human mobility patterns show a high degree of temporal and spatial regularity, the COVINDEXT should not exceed the value 0 without NPIs implemented. That is what we obtain. The maximum value determined here is 0.05.

³⁰ The greater differences across states are observed in May. We only obtain positive values in March but not in April and May, see Figure A2 in the Appendix A. States with positive values in March are Alaska, Louisiana, Maryland, New Jersey, New Mexico, New York, North Carolina, Oregon, Utah, Virginia, and Washington.

³¹ The COVINDEXT increases from April to May for Alabama, Alaska, Georgia, Iowa, Maine, Minnesota, Montana, Nebraska, Nevada, North Dakota, Ohio, South Carolina, Texas, Utah, and Wyoming.

concentrated in the North-East, East-North Central and Pacific (California).

Depending on the use of the location places (recreation, shopping, business, transportation...), one can foresee a differential impact of the NPIs examined on the labor outcomes. This can be problematic in the case of the category of mobility park, which appears to respond in a different way to the NPIs. For example, after the school closures, it is observed a positive and statistically significant impact of this measure in this category of mobility in 20 states. Although the higher the mobility in parks, the lower the effectiveness of the NPIs, it can be argued that this simply reflects the closure of other out-of-home places. Then, the higher the mobility in parks, the lower the employment and the hours worked. To address this issue, we have built our COVINDEX without the category Park and results are maintained (see Table B7 in Appendix B).³²

3. Empirical Strategy and Identification

Our objective is to explore the extent to which NPIs, adopted to curb the spread of the COVID-19, paused the public sector employment, and to examine whether the public sector was more/less affected than the private sector. We analyze heterogenous impacts across different groups by race, gender and level of education and the channels through which the NPIs are more likely to be operating in job traits. We examine both fluctuations in the propensity to be employed (at work) and in hours worked (measured in logarithm), in this last case for individuals reporting working during the reference week. Our model exploits the temporal and geographic variation as well as the differences in the intensity of the NPIs to identify their impact on labor outcomes as follows:

$$Y_{ismt} = \alpha + \beta COVINDEX_{sm}^{2020} + X_{ismt}\gamma + \delta_t + \varphi_m + \theta_s + \varepsilon_{ismt} \quad (3)$$

with Y_{ismt} being the labor outcome of interest, that is, whether individual i is employed (or the

³² The Pearson correlation of both indices is 0.87. We have also tested whether the decrease in the mobility have a different effect on the labor outcomes depending on the category of mobility considered. We have used the minimum value for each category of mobility and we have run regressions on the labor outcomes of interest. The results are presented in table C1 in the Appendix C. We observe the same direction in the relationship. We have also checked this using the average minimum drop in the mobility by state and month considering all categories together, see Panel F in table C1 in the Appendix. Once again, the direction of the relationship is maintained which gives us confidence in including all categories of mobility together in the COVINDEX.

logarithm of weekly hours worked) in state s , month m and year t . The variable $COVINDEX_{sm}^{2020}$ is the index capturing the intensity of the NPIs measured in terms of the duration of the NPIs and weighted by the estimated share of the population that changes mobility patterns as a consequence of the NPIs at the state and month levels in 2020. All specifications include demographic characteristics (X_{ismt}) known to affect the labor force status, including gender, age, educational attainment, marital status and whether there are children in the household.³³ When focusing on those reporting to be employed, the vector X_{ismt} also includes controls for the occupation held.³⁴ It also includes a set of state and time (year, month) fixed-effects (δ_t , φ_m and θ_s) that control for unobserved factors potentially affecting employment outcomes. ε_{ismt} is the error term. Data Appendix explains in detail how these variables are defined.

We focus our attention on the coefficient β , which captures the impact of the COVINDEX on the labor outcomes of the public sector. It can be surmised that this coefficient can be biased due to the unlikely random declaration (and expiration, if any) of NPIs throughout the U.S. The spread of the COVID pandemic as well as the party affiliation of governors of U.S. states and the division of their partisans can be factors that determined the implementation of the NPIs (Adolph et al., 2020; Allcott et al., 2020; Gupta, Nguyen, et al., 2020).³⁵ For instance, states with higher employees in the public sector could delay or even avoid the closure of some activities due to fear of decreasing their future revenues. If that were the case, the estimated impact of the COVINDEX might be downward biased. While recognizing likely non-random adoption of NPIs, what matters here in terms of inference purposes is the possible endogeneity with regards to the outcomes of interest. To tackle this issue, we conduct an event study for each of the labor market

³³ Results prove robustness to the exclusion/inclusion of these controls.

³⁴ For the propensity of being at work, occupation might be correlated with the error term because, for example, the same unobservable characteristics that affect occupational choice in the public sector also influences the likelihood that an individual will lose his/her job (Gittleman & Pierce, 2012). Being aware of this possible problem, we did not include these controls in the analysis of the propensity of being employed although we include them in the case of hours worked. To probe this further, we have run simple robustness checks adding/deleting occupation controls and results do not vary, see Appendix B Table B8.

³⁵ As mentioned above, to assess for whether we partly capture voluntary changes in the mobility patterns of individuals with our COVINDEX, we have controlled for the evolution of the COVID-19 by adding an indicator variable for the first COVID-19 death by state to calculate the weights of the COVINDEX. Our findings are not undermined.

outcomes being examined. This allows us to gauge if any impact of NPIs on labor market outcomes in the public sector predated the adoption of effective, in terms of mobility, policies (Goodman-Bacon & Marcus, 2020). Since our empirical strategy is based on mobility pattern changes in the share of population affected by the NPIs, we conduct an event-study model that defines the leads as the periods before the COVINDE_X first turned to a non-zero value. The lags are interacted with the COVINDE_X to capture the intensity of NPIs, using a similar methodology to those works that consider continuous treatment variables (Clemens et al., 2018; Goodman-Bacon, 2018). Formally, the event-study model is defined as follows:

$$Y_{ismt} = \sum_{r=-15}^{-2} \tau_r 1\{t^m - t_e^m = r\} + \sum_{r=0}^2 \rho_r \left[1\{t^m - t_e^m = r\} \cdot COVINDE_{sm}^{2020} \right] + X_{ismt}\gamma + \delta_s + \varphi_m + \theta_t + \varepsilon_{ismt} \quad (4)$$

where Y_{ismt} is the outcome for individual i in state s , month m and year t . With pre/post event defined by dummy variables $1\{t^m - t_e^m = r\}$ that measure the time ($t^m=1$ (January 2019), ..., $t^m=17$ (May 2020)) relative to the $COVINDE_{sm}^{2020}$ first turned to a non-zero value (t_e^m). The reference period in all event studies is the period before the event occurred (in our case when the index first turned to a non-zero value), when $r = -1$. We examine the existence of pre-trends by coefficients τ_r . The coefficients ρ_r measure the dynamics of NPIs effects, and they are interacted with the $COVINDE_{sm}^{2020}$ to capture the intensity effects. The rest of the variables are defined as in Equation (3). The length of the event-time “window” is not so long in comparison to those papers using data since 2015 or 2016 (Béland et al., 2020) to avoid bias in the coefficients because of composition change of groups in the pre-event.³⁶

To test further that the adoption of the NPIs are not endogenous to the labor market outcomes of interest (reverse causality), we also examine whether the number of days that elapse since the first death until the first NPI can be predicted by our outcomes of interest. To that end,

³⁶ A long window might be problematic in the case of the U.S. public sector since the last Great Recession has significantly lagged the private sector in recovery. Total public sector employment did not recover its levels of 2008 until 2019 (Hinkley, 2020).

we collapse our data at the state level and use as the dependent variable the number of days between first COVID-19 death in U.S. and first NPI in each state. Formally:

$$\text{Days until first NPI}_s = Y_s \vartheta + \rho_R + \varepsilon_s \quad (5)$$

The vector Y_s represents the average level of labor outcomes (namely, the employment rate in pre-COVID period (January 2019 to February 2020), or hours worked in logarithm) in the state s . The model includes fixed effects, ρ_R , for each of the nine U.S. regions (i.e. New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific) since we cannot include state fixed effects. ε_s is the error term.

4. Labor Market Impacts of NPIs

4.1 Main Findings

Table 2 presents the estimation of Equation (3) that shows the impact of NPIs on public sector labor outcomes.³⁷ We observe that the increase in the intensity of the NPIs (the lower the values of the COVINDEX, the higher the intensity of NPIs) that occurs since March 2020 did affect the public sector labor outcomes significantly, through a reduction in the propensity of being a public sector employee and a drop in the hours worked. Among individuals living in a typical state with the average COVINDEX, (-1.02, post-COVID), the propensity of being at work significantly reduces by 5% with respect to the pre-COVID period.³⁸ While the weekly hours of work only decrease by 1.3% for those at work. NPIs appear to mainly lower the propensity of being an employee (at work) in the public sector but the hours worked (for a sample of individuals working in the pre/post-COVID) does not change so much.

An aforementioned concern with the results reported in Table 2 refers to the possibility that our coefficient of interest, which captures the impact of the COVINDEX, might be biased due to the unlikely random implementation of the NPIs. To mitigate this, we examine if any

³⁷ All coefficients incorporated in the specifications can be seen in the Appendix C in Table C2.

³⁸ Indiana has a quite close to the average COVINDEX. This state passed the five NPIs and with the out of home mobility decreasing on average to a minimum of -4% in March, -41% in April, -32% in May.

impact of NPIs on labor market outcomes in the public sector predated the adoption of effective NPIs in terms of mobility (Goodman-Bacon & Marcus, 2020). We made a generalization of the model presented in equation (3) that can reveal biases caused for reverse causality and/or voluntary precautions (Goodman-Bacon & Marcus, 2020), see Equation (4). Event-study estimates are presented in Table 3. There is little evidence of significant differential pre-trends. All estimates for the months prior to the COVINDEX first turns non-zero value (which happens when NPIs are effective in changing mobility patterns) are not statistically significant and close to zero especially in the case of hours worked, strongly supporting the assumption of no pre-trends. Since post-event coefficients also capture variations in the intensity of the NPIs, the break (evaluated in the average value of the COVINDEX) which, as in the case of the estimates shown in Table 2, appears to be clearer in the case of employment than in the case of hours worked, for which we do not observe a coefficient statistically different from zero in the last period (two months after the event). The rest of post-event coefficients are all statistically different from zero, even one and two months after the NPIs enforcement were effective.

The possible reverse causality, because of the potential endogenous nature of NPIs with respect to the public sector labor market outcomes considered here, can also be checked by modelling the timing of NPIs as a function of the state's public sector activity prior to COVID-19 (January 2019 to February 2020). This allows us to examine if, while possible non-random, the NPIs adoption can be predicted by our labor outcomes of interest. The results on the estimation of Equation (5) are shown in Table C3 of the Appendix. As can be observed, there is significant evidence to reject that the timing of NPIs is explained by the pre-COVID employment rate of those reporting working/or last work in the public sector or the average weekly worked hours for those at work in the public sector. We feel comforting with our findings since all this empirical evidence suggests that the adoption of the NPIs, while likely non-random, does not appear to be correlated with the labor outcomes examined in our work.

Because the impact of the NPIs is not limited to the public sector, we wonder whether those salaried workers in the public sector (the group examined here) are differentially affected by the NPIs than those working for a wage in the private sector or/and self-employed workers.

This is interesting due to the traditional job security of the public sector jobs during an economic recession (Farber, 2010). The results are reported in Table 4 classifying the Panels by class of worker (public, private, self-employed). As explained above, the propensity of being at work in the public sector significantly decrease by 5% with respect to the pre-COVID period for individuals residing in a typical state, this reaches the 9% of reduction for those in the private sector and 12% in the case of self-employed workers. For the weekly worked hours of those at work, the reduction was 1.3% in the public sector which is not statistically different from the drop in the private sector (1.6%). The self-employed workers appear to be significantly in danger considering the average COVINDEX by a 6%. This is in line with the works suggesting that self-employed workers have been particularly hit not only in the U.S. but also in other countries such as the UK (Adams-Prassl et al., 2020; Blundell & Machin, 2020; Kalenkoski & Pabilonia, 2020). Adams-Prassl et al. (2020) using real time data survey find that employees in salaried jobs are 6 percentage points less likely to lose their jobs relative to non-salaried employees as a consequence of the COVID-19 pandemic. Unlike economic crisis, the public sector appears to behave in a procyclical way during this pandemic but it still maintained significantly higher job security than those salaried private employees and specially than self-employed workers.

Up to here, we have left out the analysis of how NPIs impact workers who report having a job but being absent, being aware of the problematic misclassification of some workers in this category, we have extended our work to this issue since other works consider important their analysis (Montenovo et al., 2020). It should be noted that, in this case, comparison among categories (salaried vs. self-employed worker) is tricky and we avoid it here due to the fact that for self-employed workers who are business owners without having another job, the “on layoff (temporary or indefinite)” response option is not available according to the CPS criteria, (BLS June 2020).³⁹ They are included in the category having a job but not at work for reasons related to the coronavirus, which can explain the huge previously described differences observed in the raw data, Table 1. For individuals living in a typical state having applied NPIs with an intensity

³⁹ https://www.bls.gov/news.release/archives/empsit_07022020.pdf (Updated July 2020)

equal to the average COVINDEX in the post-COVID period, the propensity of having a job but being absent increased by 30% in the salaried public sector workers, 68% in the private sector, and most than double in the case of self-employed workers with respect to the pre-COVID period.

5. Heterogeneous Impacts

5.1. Gender, Race, and Education

With the purpose of exploring the differential effects of NPIs on the public sector labor outcomes of different subgroups of the population, we repeat our analyses separating the sample by gender, race, and educational attainment. This allows us to study whether the historical role of the public sector in the U.S. as an equalizing institution (Laird, 2017), through job opportunities for minority workers, especially black people and women, has been altered as a consequence of the pandemic. What literature shows is that, in the aftermath of the last Great Recession, the job security of working in the public sector appears to be substantially reduced for minority workers (Laird, 2017).

Cuts to the public sector workforce might be of particular concern for women, who traditionally have been less exposed to job losses than men during an economic recession. During the pandemic, prior evidence on real-time surveys points to the opposite. Women are hardly hit (Adams-Prassl et al., 2020), in part because they are more penalized by some of the NPIs such as school closures which increase the necessities of childcare (Biroli et al., 2020; Del Boca et al., 2020; Farré et al., 2020; Sevilla & Smith, 2020). Table D1 in Appendix D shows the results after differentiating among men and women. Not surprisingly, among women living in a typical state with the average COINVDEX (-1.02) their propensity of being employee (at work) in the public sector reduces by 5.6% whereas among men by 4.4% relative to the pre-COVID period while the opposite occurs in the case of worked hours. Labor impact of NPIs appears to occur in a double side, reducing the propensity of being at work and hours worked conditional on working (1.5% vs. 1.2%) but there are no statistically significant differences between men and women in the public sector. It is interesting, however, that men and women in the public sector are statistically less heavily hit than their counterparts in private and self-employed works. The magnitude of the impact of the NPIs on the gender differential response is lower than observed during the

pandemic, only in April being a woman was associated to a 3.3 percentage point increase in layoff rates relative to men according to Montenegro et al. (2020). This may indicate that other reasons apart from the intensity of NPIs are driving the different response to the COVID-19 pandemic among men and women.

The double punishment of the NPIs on the public sector labor outcomes is also observed among white and black individuals but not among individuals of other races for which the readjustment only appears to occur through a reduction in the propensity of being at work, see Table D2 in Appendix D. It is interesting to see that in an equalizing institution such as the public sector where all races have a similar propensity of being at work in the pre-COVID period, the pandemic has not broken this trend, the apparent dissimilarities in the reduction of their propensity of being at work relative to the pre-COVID period (5.8% vs. 4.7%) between black and white are not statistically different from zero neither in the case of hours worked (1.9% vs. 1.2%). In any case, this is sizable in comparison with the estimated drop of 4% in the likelihood of being employed in the public sector from 2008 to 2011 among black individuals but also for white for which the estimated drop was around 1% (Laird, 2017). Black self-employed workers are three times (only 2 times in the case of white people) more likely to report not being at work than those in the public sector relative to the pre-COVID period in a typical state (5.8% vs. 18.7%), which may suggest higher job security for this collective in the public sector.

We also observed notable statistically significant differences between people with and without a university education. Labor outcomes of low educated individuals (less than college degree) have been the largest hit so far by the NPIs regardless of being salaried worker in the public/private sector or self-employed worker, Table D3 in Appendix D. This is in line with the findings of Adams-Prassl et al., (2020). What is again noticeable is that those in the public sector are again the less affected by the NPIs, especially among those with some college or more (the largest group (81%) of workers in the public sector) who are almost three times less likely to report not being at work than self-employed workers and the NPIs impact on hours worked is almost 0.

In sum, NPIs appear to double impact the labor situation of men and women without differences in the public sector. The impact of the NPIs is not more remarkable among minorities, but it is among low educated in the public sector. In any of the sub-population considered, workers in the public sector are the less heavily hit by the NPIs in comparison to salaried workers in the private sector or self-employed workers (the worst so far). This heterogeneity may indicate that workers in the public sector are in occupations with more opportunities for remote work or that they work in the essential jobs. We revisit this issue in the next sub-section.

5.2. NPIs and jobs traits

Once we have analyzed whether some of the well-known labor market inequalities caused by characteristics of the population can be exacerbated by the NPIs. Surely, policymakers would be concerned about how NPIs differentially hit inside the three levels of the U.S. public sector (federal, state, and local government). Two huge sticking points arise: the composition of the employment in each government level and the government funding. Although apparently, the objectives of the stimulus packages passed under the U.S. state of emergency (March 13th) are focused on *protecting the American people from the public health and economic impacts of COVID-19* (U.S. Department of the Treasury), the vast majority of local governments (cities and counties) have received inadequate or no federal aid according to the NACo (National Association of Counties) and the NLC (National League of Cities).⁴⁰ The over \$2 trillion economic relief package operating under the Coronavirus Aid, Relief, and Economic Security (CARES) Act (March 27th) established a \$150 billion Coronavirus Relief Fund (CRF) for state, county and municipal governments with populations of over 500,000 people to use for necessary expenditures incurred due to the COVID-19 public health emergency, but not to fill shortfalls in government revenue to cover expenditures that would not otherwise qualify under the statute. Less than 5% of the counties were eligible to direct payments and nearly 70% of cities have not yet received funding through the CARES Act, with 24 states without any plan to allocate the CRF

⁴⁰ <https://home.treasury.gov/policy-issues/cares>

to local governments by June 2020.⁴¹

With regards to our analysis, since local governments appear to be incurring unbudgeted COVID-19-related expenditures with no funding or inadequate and supporting a large public workforce (payroll, retirement and workers compensation account for nearly half of city budgets in 2017 according to the NLC), we would expect that NPIs intensity hard hit our outcome of interest at this level of government.⁴² This is what we find in Table D4 in Appendix D, local employee appears to be double hit. Their propensity of being at work declined by 6.3% in a typical state (with the average COVINDEX) with respect to the pre-COVID period whereas only by 3.7% and 4% among state and federal employees, respectively. Only local employees reduce the worked hours by 2.1% (conditional on working). In contrast, our estimates for the state and federal employees are close to zero and not statistically significant suggesting no change.

It is also arguable that much of the distinct impact of NPIs on the public sector, in comparison with salaried private and self-employed workers, is probably driven by the particular traits of government jobs if, for example, many of their workers are in essential activities (such as public health services), or/and if there are more possibilities to remote work in the public sector (education). As a first step to examine this, Table D5 in Appendix D account for the type of job held by the CPS's respondents. We split the sample between essential/non-essential workers.⁴³ Not surprisingly, a less dramatic picture is observed with those classified as essential for all

⁴¹ See: <https://www.naco.org/resources/counties-matter-covid-19> (Updated July 2020). Data at the city level come from a survey conducted between June 8-June 16, 2020 in a total of 1,117 cities, towns and villages from all 50 states, the District of Columbia and Puerto Rico. <https://www.nlc.org/sites/default/files/users/user52651/CAE-Local-Impact-Survey-One-Pager.pdf>

⁴² https://covid19.nlc.org/wp-content/uploads/2020/06/What-Covid-19-Means-For-City-Finances_Report-Final.pdf (Updated July 2020)

⁴³ The official industry guidelines issued by the Department of Homeland Security through the Cybersecurity and Infrastructure Security Agency (CISA) provided an advisory guidance to identify the critical infrastructure sectors and the essential workers. However, the CISA classification (without any official codification) cannot be easily merged with the detailed Industry Classification Codes of the CPS. For this reason, we opt for the classification of essential workers of two states Pennsylvania and Delaware (this information is provided by the NGA) that use the official NAICS codes which can be easily matched with the CPS Codes using BLS equivalence for the years 2019 and 2020. We define essential workers as those working in an industry classified as essential by both states, and as non-essential otherwise. We admit likely measurement error because not all states use the same classification of essential workers, but this is a much more precise way of determining essential industries than a possible subjective partial classification made manually from the CISA.

salaried public/private and self-employed workers. It is interesting, however, that NPIs do not appear to have heavily impacted the essential workers in the public sector, with 3 (2) times less probability of not being at work than self-employed workers (salaried private workers), and, for those working, with an impact negative albeit almost zero in their worked hours. Similarly, once again, non-essential workers appear to have great job security in the public sector at least to be at work, with salaried private employees and self-employed workers nearly doubling the reduction of the propensity of not being at work. In any case, we recognize that this should be taken with caution since the classification of essential workers do not distinguish between public/private sector and the composition of the public workforce differs from that of the private sector.

To deeply explore whether part of the public workforce is being hardly hit, we distinguish between workers in the Health Care and Social Assistance, Education, and Others. An additional job descriptor is added to this analysis that has played an important role during the pandemic: occupations that are allowed to telework or are not.⁴⁴ We divide the sample between this characteristic (telework) and then incorporated interactions of our variable of interest (COVINDEX) with the industries mentioned above. Table D6 in Appendix D presents the results. The most notable finding, although no unexpected, is the no significant impact (and close to zero) of NPIs on labor outcome variables for those that are not able to telework in the Health Care and Social Assistance inside the public sector. Then, the different intensity in the NPIs is not driving the evolution of Health Care and Social Assistance workers who cannot telework at least in the public sector (which are expected to be in the front line of the pandemic). In contrast, in Education those who are not allowed to telework are double hardly hit in the propensity of being at work and in the worked hours in the public sector. In other industries, the readjustment is observed only in the propensity of being at work but not in the hours worked. Again, those in the public sector are less heavily hit or similarly hit (no significant difference from zero) regardless of the industry and the ability to telework.

⁴⁴ We classify the feasibility of working at home (telework) for all occupation categories following the classification of Dingel & Neiman (2020) merging the Standard Occupational Classification (SOC) codes and the CPS occupational codes with the equivalence provided by the BLS in 2019 and 2020.

6. Conclusions

Unlike recent economic recessions in the U.S., the public sector has quickly responded to the pandemic crisis by furlough and/or temporary laid-off their workers behaving in a similar way to the private sector. This is doubtless by simply looking at the raw data on the evolution of the employment in the public/private sector, however, what is not so clear is to what extent the distinct intensity of the NPIs, implemented to contain the spread of the COVID-19, has hit the public sector labor outcomes. In this work, we document that the NPIs enforcement in a typical state during the COVID-19 reduces the likelihood of being employed (at work) by 5% with respect to the pre-COVID period and the hours worked by 1.3%. Despite being hit, we have shown evidence pointing to the public sector as still maintaining job security for salaried employees since the propensity of being at work is significantly reduced in 4 percentage point less than in the private sector and in 14 percentage points less than among self-employed workers with respect to the pre-COVID period.

To determine these findings, we have had to develop a novel index (COVINDEX) that allows us to easily gauge the intensity of the NPIs by using one intensity measure for each state and month. Since NPIs have varied in space, scale, and time, we have used high-frequency-real-time on mobility from Google to proxy the intensity of NPIs without relying our findings on assumed homogeneity and effectiveness of NPIs. The COVINDEX is an aggregate weighted index of the daily average effect of each NPIs on the relative change of the total number of visitors in five set of locations out of the place of residence.

Although the adoption of NPIs can be likely non-random, we feel confident in our estimates since we do not observe significant evidence on the existence of pre-COVID trends by conducting event-study models on our outcomes of interest. Additionally, pre-COVID differences across states in the labor outcomes of interest do not appear to predict the date in which the NPIs are adopted. We also probe further our results with an extensive number of robustness.

In terms of heterogeneity analysis, NPIs appear to double impact (on employment propensity and hours worked) the labor situation of men and women without significant

differences among both of them. The impact of the NPIs is more remarkable among the lower educated in the public sector but no differences are observed between white and black people. In all cases, regardless of the demographic traits or level of education, workers in the public sector appear to be less heavily hit than other salaried workers in the private sector and self-employed workers (the worst so far).

We only document the impact of NPIs on the public sector workforce in the short run. Admittedly, it is too early to determine whether the negative consequences of the pandemic crisis on the public sector workforce are going to be lasting. However, while the federal economic stimulus continues, there is no any new aid to state and local governments and the expected budget shortfall only at the local government level (which is significantly the most affected) reach \$360 billion (\$1 trillion if it is considered the rest of government levels) for the year 2020 according to the NLC. Then, the negative impacts could grow deeper every day with those public sector workers in the Health Care and Social Assistance (in the front line of the pandemic) and who cannot telework being the only ones for which the intensity of the NPIs has had no effect. If the adjustment in public budgets takes place with the destruction of public sector employment, this could lead to more pronounced the future negative effects of the NPIs on the private sector. The public sector crisis can mitigate the multiplier effect of public employment, especially in the tradable sector (Faggio & Overman, 2014; Jofre-Monseny et al., 2020). Decreasing the number of public employees living in a city may decrease the demand for services such as housing, restaurants, which in turn reduces private employment, although this may be partly compensated by decreases in local wages and prices that might follow the public employment reduction.

It is also true that the framework under which U.S. local and state governments are operating is much more flexible (with early responses on the public employment) which could, in part, improve their possible budget constraints. This is not happening in other countries (such as Spain) at least as badly hit as the U.S. by the pandemic where there has been no readjustment in public employment.

References

- Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189, Article 13183. <https://doi.org/10.1016/j.jpubeco.2020.104245>
- Adolph, C., Amano, K., Bang-Jensen, B., Fullman, N., Wilkerson, J., Dieleman, J., Greer, S., Grumbach, J., Keller, E., Kiessling, K., Pigott, D., & Singer, P. (2020). Pandemic Politics: Timing State-Level Social Distancing Responses to COVID-19. *APSA Preprints*. <https://doi.org/10.33774/apsa-2020-sf0ps>
- Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., & Yang, D. (2020). Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic. *Journal of Public Economics*. <https://doi.org/10.1016/j.jpubeco.2020.104254>
- Amuedo-Dorantes, C., Arenas-Arroyo, E., & Sevilla, A. (2018). Immigration enforcement and economic resources of children with likely unauthorized parents. *Journal of Public Economics*, 158, 63–78. <https://doi.org/10.1016/j.jpubeco.2017.12.004>
- Amuedo-Dorantes, C., Borra, C., Rivera-Garrido, N., & Sevilla, A. (2020). *Timing is Everything when Fighting a Pandemic: COVID-19 Mortality in Spain* (No. 13316; IZA DP). <https://www.iza.org/publications/dp/13316/timing-is-everything-when-fighting-a-pandemic-covid-19-mortality-in-spain>
- Amuedo-Dorantes, C., & Lopez, M. J. (2015). Falling through the cracks? grade retention and school dropout among children of likely unauthorized immigrants. *American Economic Review*, 105(5), 598–603. <https://doi.org/10.1257/aer.p20151113>
- Badr, H. S., Du, H., Marshall, M., Dong, E., Squire, M. M., & Gardner, L. M. (2020). Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. *The Lancet Infectious Diseases*. [https://doi.org/10.1016/S1473-3099\(20\)30553-3](https://doi.org/10.1016/S1473-3099(20)30553-3)
- Baek, C., Mccrory, P. B., Messer, T., & Mui, P. (2020). *Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data* (No. 101–20; IRLE WORKING PAPER). <http://irle.berkeley.edu/files/2020/04/Unemployment-Effects-of-Stay-at-Home-Orders.pdf>
- Barro, R. J., Ursúa, J. F., Weng, J., & Everlife, J. W. (2020). *The Coronavirus and the Great Influenza Pandemic: Lessons from the “Spanish Flu” for the Coronavirus’s Potential Effects on Mortality and Economic Activity* (No. 26866; NBER Working Paper). <https://www.nber.org/papers/w26866>
- Bayham, J., & Fenichel, E. P. (2020). Impact of school closures for COVID-19 on the US health-care workforce and net mortality: a modelling study. *The Lancet Public Health*, 5(5), e271–e278. [https://doi.org/10.1016/S2468-2667\(20\)30082-7](https://doi.org/10.1016/S2468-2667(20)30082-7)
- Béland, L.-P., Brodeur, A., & Wright, T. (2020). *COVID-19, Stay-At-Home Orders and Employment: Evidence from CPS Data* (No. 13282; IZA DP). <https://www.iza.org/publications/dp/13282/covid-19-stay-at-home-orders-and-employment-evidence-from-cps-data>
- Biroli, P., Bosworth, S. J., Della Giusta, M., Di Girolamo, A., Jaworska, S., & Voleen, J. (2020). *Family Life in Lockdown* (No. 13398; IZA ZP). <https://www.iza.org/publications/dp/13398/family-life-in-lockdown>
- Blundell, J., & Machin, S. (2020). *Self-employment in the Covid-19 crisis* (No. 3). Article 3. <http://cep.lse.ac.uk/pubs/download/cepcovid-19-003.pdf>
- Bootsma, M. C. J., & Ferguson, N. M. (2007). The effect of public health measures on the 1918 influenza pandemic in U.S. cities. *Proceedings of the National Academy of Sciences of the United States of America*, 104(18), 7588–7593. <https://doi.org/10.1073/pnas.0611071104>
- Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. J. (2020). *A Literature Review of the Economics of COVID-19* (No. 13411; IZA DP, Issue 13411). <https://www.iza.org/publications/dp/13411/a-literature-review-of-the-economics-of-covid-19>
- Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M. (2020). *How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data*. https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

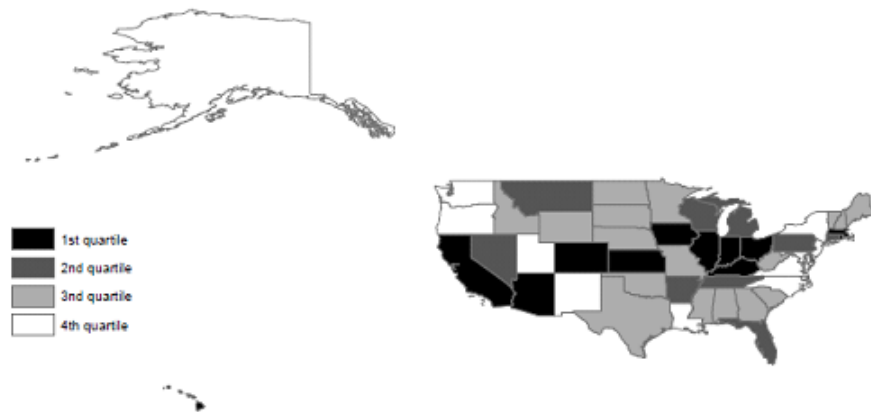
- Clemens, M. A., Lewis, E. G., & Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the Mexican Bracero exclusion. *American Economic Review*, 108(6), 1468–1487. <https://doi.org/10.1257/aer.20170765>
- Correia, S., Luck, S., & Verner, E. (2020). Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3561560>
- Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong Social Distancing Measures In The United States Reduced The COVID-19 Growth Rate. *Health Affairs*, 39(7), 1237–1246. <https://doi.org/10.1377/hlthaff.2020.00608>
- Cowan, B. (2020). *Short-run Effects of COVID-19 on U.S. Worker Transitions* (No. 27315; NBER Working Paper). <https://doi.org/10.3386/w27315>
- Craig, S. G., & Hoang, E. C. (2011). State government response to income fluctuations: Consumption, insurance, and capital expenditures. *Regional Science and Urban Economics*, 41(4), 343–351. <https://doi.org/10.1016/j.regsciurbeco.2011.02.005>
- Dave, D., Friedson, A., Matsuzawa, K., & Sabia, J. (2020). When Do Shelter-in-Place Orders Fight COVID-19 Best? Policy Heterogeneity Across States and Adoption Time. In *Psychology Applied to Work: An Introduction to Industrial and Organizational Psychology, Tenth Edition Paul* (Vol. 53, Issue 9). <https://doi.org/10.3386/w27091>
- Del Boca, D., Oggero, N., Profeta, P., & Rossi, M. C. (2020). *Women's Work, Housework and Childcare, before and during COVID-19* (No. 13409; IZA DP). <https://www.iza.org/publications/dp/13409/womens-work-housework-and-childcare-before-and-during-covid-19>
- Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189. <https://doi.org/10.1016/j.jpubeco.2020.104235>
- Faggio, G., & Overman, H. (2014). The effect of public sector employment on local labour markets. *Journal of Urban Economics*, 79, 91–107. <https://doi.org/10.1016/j.jue.2013.05.002>
- Farber, H. S. (2010). *Job Loss and the Decline in Job Security in the United States* (K. G. Abraham, J. R. Spletzer, & M. Harper (eds.); pp. 223–262). University of Chicago Press.
- Farboodi, M., Jarosch, G., & Shimer, R. (2020). *Internal and External Effects of Social Distancing in a Pandemic* (No. 27059; NBER Working Paper). <https://doi.org/10.3386/w27059>
- Farré, L., Fawaz, Y., González, L., & Graves, J. (2020). *How the COVID-19 Lockdown Affected Gender Inequality in Paid and Unpaid Work in Spain* (No. 13434; IZA DP). <https://www.iza.org/publications/dp/13434/how-the-covid-19-lockdown-affected-gender-inequality-in-paid-and-unpaid-work-in-spain>
- Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. (2020). Integrated Public Use Microdata Series, Current Population Survey. In *Version 7.0 [dataset]*. <https://doi.org/https://doi.org/10.18128/D030.V7.0>
- Fontaine, I., Galvez-Iniesta, I., Gomes, P., & Vila-Martin, D. (2020). Labour market flows: Accounting for the public sector. *Labour Economics*, 62. <https://doi.org/10.1016/j.labeco.2019.101770>
- Forsythe, E., Kahn, L. B., Lange, F., & Wiczer, D. (2020). Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims. *Journal of Public Economics*. <https://doi.org/10.1016/j.jpubeco.2020.104238>
- Fullman, N., Bang-Jensen, B., Reinke, G., Magistro, B., Amano, K., Adolph, C., & Wilkerson, J. (2020). *State-level social distancing policies in response to COVID-19 in the US* (1.67). <http://www.covid19statepolicy.org>
- Gagnon, A., Miller, M. S., Hallman, S. A., Bourbeau, R., Herring, D. A., Earn, D. J., & Madrenas, J. (2013). Age-Specific Mortality During the 1918 Influenza Pandemic: Unravelling the Mystery of High Young Adult Mortality. *PLoS ONE*, 8(8), e69586. <https://doi.org/10.1371/journal.pone.0069586>
- Gittleman, M., & Pierce, B. (2012). Compensation for State and Local Government Workers. *Journal of Economic Perspectives*, 26(1), 217–242. <https://doi.org/10.1257/jep.26.1.217>
- González, M. C., Hidalgo, C. A., & Barabási, A. L. (2008). Understanding individual human

- mobility patterns. *Nature*, 453(7196), 779–782. <https://doi.org/10.1038/nature06958>
- Goodman-Bacon, A. (2018). Public Insurance and Mortality: Evidence from Medicaid Implementation. *Journal of Political Economy*, 126(1), 216–262. <https://doi.org/10.1086/695528>
- Goodman-Bacon, A., & Marcus, J. (2020). *Using Difference-in-Differences to Identify Causal Effects of COVID-19 Policies* (No. 1870; DIW Berlin Discussion Paper). Elsevier BV. <https://doi.org/10.2139/ssrn.3603970>
- Goodman, C. J., & Mance, S. M. (2011). Employment loss and the 2007–09 recession: an overview. *Monthly Labor Review*, April, 3–12. <https://www.bls.gov/opub/mlr/2011/04/art1full.pdf>
- Google LLC. (2020). *Google COVID-19 Community Mobility Reports*. https://www.google.com/covid19/mobility/data_documentation.html?hl=en
- Gupta, S., Montenegro, L., Nguyen, T., Rojas, F. L., Schmutte, I., Simon, K., Weinberg, B., & Wing, C. (2020). *Effects of Social Distancing Policy on Labor Market Outcomes* (No. 27280; NBER Working Paper). <https://doi.org/10.3386/w27280>
- Gupta, S., Nguyen, T., Rojas, F. L., Raman, S., Lee, B., Bento, A., Simon, K., & Wing, C. (2020). *Tracking Public and Private Responses to the COVID-19 Epidemic: Evidence from State and Local Government Actions* (No. 27027; NBER WORKING PAPER). <https://doi.org/10.3386/w27027>
- Hatch, J. (2004). Employment in the public sector: two recessions' impact on jobs. *Monthly Labor Review*, October, 38–47.
- Hatchett, R. J., Mecher, C. E., & Lipsitch, M. (2007). Public health interventions and epidemic intensity during the 1918 influenza pandemic. *Proceedings of the National Academy of Sciences*, 104(18), 7582–7587. <https://doi.org/10.1073/pnas.0610941104>
- Hinkley, S. (2020). *Public Sector Impacts of the Great Recession and COVID-19* (Center for Labor Research and Education). <http://laborcenter.berkeley.edu/public-sector-impacts-great-recession-and-covid-19/>
- Jofre-Monseny, J., Silva, J. I., & Vázquez-Grenno, J. (2020). Local labor market effects of public employment. *Regional Science and Urban Economics*, 82, 1–20. <https://doi.org/10.1016/j.regsciurbeco.2018.11.001>
- Kalenkoski, C. M., & Pabilonia, S. W. (2020). *Initial Impact of the COVID-19 Pandemic on the Employment and Hours of Self-Employed Coupled and Single Workers by Gender and Parental Status* (No. 13443; IZA DP, Issue 13443). <http://ftp.iza.org/dp13443.pdf>
- Kopelman, J. L., & Rosen, H. S. (2016). Are Public Sector Jobs Recession-proof? Were They Ever? *Public Finance Review*, 44(3), 370–396. <https://doi.org/10.1177/1091142114565042>
- Laird, J. (2017). Public Sector Employment Inequality in the United States and the Great Recession. *Demography*, 54(1), 391–411. <https://doi.org/10.1007/s13524-016-0532-4>
- Markel, H., Lipman, H. B., Navarro, J. A., Sloan, A., Michalsen, J. R., Stern, A. M., & Cetron, M. S. (2007). Nonpharmaceutical interventions implemented by US cities during the 1918–1919 influenza pandemic. *Journal of the American Medical Association*, 298(6), 644–654. <https://doi.org/10.1001/jama.298.6.644>
- Montenegro, L., Jiang, X., Rojas, F. L., Schmutte, I., Simon, K., Weinberg, B., & Wing, C. (2020). *Determinants of Disparities in Covid-19 Job Losses* (No. 27132; NBER Working Paper). <https://doi.org/10.3386/w27132>
- OECD. (2017). *Government at a Glance 2017*. OECD Publishing. https://www.oecd-ilibrary.org/governance/government-at-a-glance-2017_gov_glance-2017-en
- Painter, M., & Qiu, T. (2020). Political Beliefs affect Compliance with COVID-19 Social Distancing Orders. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3569098>
- Prem, K., Liu, Y., Russell, T. W., Kucharski, A. J., Eggo, R. M., Davies, N., Flasche, S., Clifford, S., Pearson, C. A. B., Munday, J. D., Abbott, S., Gibbs, H., Rosello, A., Quilty, B. J., Jombart, T., Sun, F., Diamond, C., Gimma, A., van Zandvoort, K., ... Klepac, P. (2020). The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. *The Lancet Public Health*, 5(5), e261–e270. [https://doi.org/10.1016/S2468-2667\(20\)30073-6](https://doi.org/10.1016/S2468-2667(20)30073-6)
- Sevilla, A., & Smith, S. (2020). *Baby Steps: The Gender Division of Childcare during the*

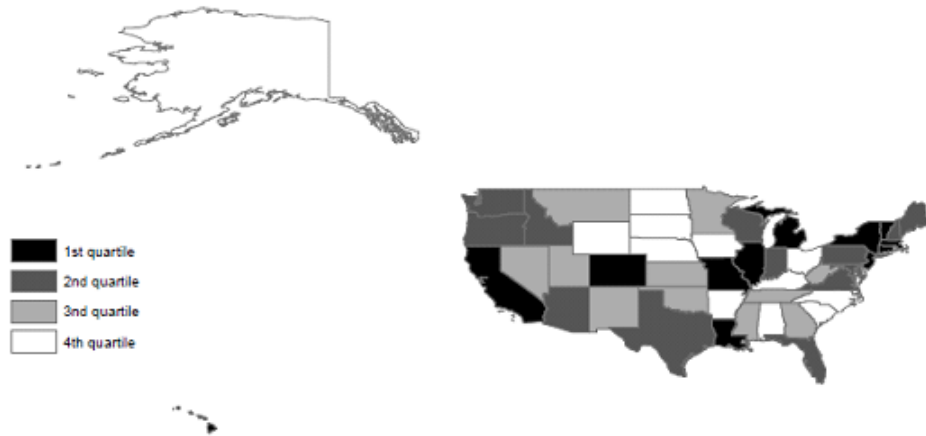
- COVID-19 Pandemic* (No. 13302; IZA DP).
<https://www.iza.org/publications/dp/13302/baby-steps-the-gender-division-of-childcare-during-the-covid-19-pandemic>
- Shanks, G. D. (2020). COVID-19 versus the 1918 influenza pandemic: different virus, different age mortality patterns. *Journal of Travel Medicine*. <https://doi.org/10.1093/jtm/taaa086>
- Wellenius, G. A., Vispute, S., Espinosa, V., Fabrikant, A., Tsai, T. C., Hennessy, J., Williams, B., Gadepalli, K., Boulanger, A., Pearce, A., Kamath, C., Schlosberg, A., Bendebury, C., Stanton, C., Bavadekar, S., Pluntke, C., Desfontaines, D., Jacobson, B., Armstrong, Z., ... Gabrilovich, E. (2020). *Impacts of State-Level Policies on Social Distancing in the United States Using Aggregated Mobility Data during the COVID-19 Pandemic*.
<http://arxiv.org/abs/2004.10172>

Figure 1: Geographic variation in the COVINDEX over time

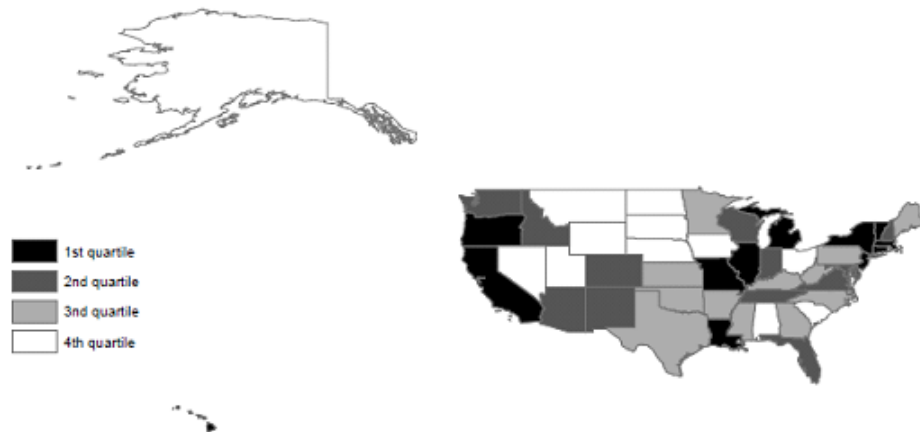
A) 13th February to 12th March (2020)



B) 13th March to 12th April (2020)



C) 13th April to 12th May (2020)



Notes: Panels A-C in Figure 1 show the evolution of COVINDEX over that time. Lighter colors correspond to lower levels of NPIs enforcement (higher levels of the COVINDEX means low effectiveness of the NPIs on reducing social interactions) in each state and month.

Table 1: Summary statistics

<i>Descriptive statistics by type of ownership of the employing organization</i>					
	01-2019/02-2020	March 2020	April 2020	May 2020	All period
Public Sector					
% Employed (At work)	92.60	91.93	84.60	88.88	91.87
% Employed (Did not work Last week)	4.49	5.17	6.00	3.64	4.57
% Unemployed	2.12	2.00	8.27	6.70	2.75
% Out of labor force	0.78	0.90	1.13	0.78	0.82
Mean work hours	38.64	38.72	38.05	38.29	38.59
Sample size	109,183	7,056	6,769	6,494	129,502
Private Sector					
% Employed (At work)	92.90	91.08	76.80	80.34	91.17
% Employed (Did not work Last week)	2.50	3.12	5.65	4.10	2.81
% Unemployed	3.73	4.87	15.66	14.04	5.06
% Out of labor force	0.86	0.93	1.89	1.52	0.97
Mean work hours	38.58	38.26	37.99	38.12	38.51
Sample size	576,385	35,698	33,295	32,201	677,579
Self-employed workers					
% Employed (At work)	92.22	89.59	72.21	77.85	90.5
% Employed (Did not work Last week)	5.03	7.00	18.59	14.14	6.48
% Unemployed	2.04	2.36	7.63	7.02	2.68
% Out of labor force	0.71	1.05	1.58	0.99	0.79
Mean work hours	38.37	37.22	35.30	36.00	38.05
Sample size	71,034	4,517	4,356	4,211	84,118
COVINDEX					
<i>Number of states with a non-zero index</i>	0	34	51	51	
Mean	0.000	-0.014	-1.448	-1.592	
S.D.	(0.000)	(0.034)	(0.392)	(-0.588)	

Notes: Weighted percentages are presented. The sample is restricted to individuals aged 18–64. Sector refers to the respondent's job at the time of the survey if the respondent is employed. For those who are unemployed or out of the labor force, sector refers to the respondent's most recent job. Number of states with the COVINDEX different from zero by the day 12th of each month. The COVINDEX range from -2.67 to 0.055.

Table 2: Main results

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.046*** (0.004)	0.013*** (0.004)
Observations	129,502	116,022
R-squared	0.041	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 3: Event study

Dependent variable	(1)	(2)
	Employed	Log (Work Hours Last Week)
15 months before the event	0.239 (0.253)	0.045 (0.146)
14 months before the event	0.216 (0.232)	0.043 (0.134)
13 months before the event	0.205 (0.212)	0.017 (0.124)
12 months before the event	0.232 (0.218)	0.030 (0.125)
11 months before the event	0.213 (0.199)	0.039 (0.119)
10 months before the event	0.182 (0.183)	0.056 (0.113)
9 months before the event	0.214 (0.163)	0.077 (0.105)
8 months before the event	0.218 (0.143)	0.084 (0.093)
7 months before the event	0.137 (0.119)	0.073 (0.079)
6 months before the event	0.114 (0.102)	0.070 (0.061)
5 months before the event	0.099 (0.079)	0.052 (0.048)
4 months before the event	0.085 (0.062)	0.037 (0.036)
3 months before the event	0.058 (0.044)	0.011 (0.019)
2 months before the event	0.028 (0.023)	-0.006 (0.012)
The month of the event x COVINDEX	0.051*** (0.009)	0.026** (0.012)
1 month after the event x COVINDEX	0.055*** (0.010)	0.012* (0.007)
2 months after the event x COVINDEX	0.042** (0.016)	0.0003 (0.009)
Observations	129,502	116,022
R-squared	0.043	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (4). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table 4: Results by type of ownership of the employing organization

<i>Panel B: Public employees</i>			
	(1)	(2)	(3)
Dependent variable	Employed	Did not Work Last Week	Log (Work Hours Last Week)
COVINDEX	0.046*** (0.004)	-0.015*** (0.003)	0.013*** (0.004)
Observations	129,502	125,051	116,022
R-squared	0.041	0.049	0.106
D.V. Mean 01/2019-02/2020	0.93	0.05	3.62
<i>Panel C: Private employees</i>			
COVINDEX	0.082*** (0.005)	-0.020*** (0.002)	0.016*** (0.002)
Observations	677,579	639,454	605,353
R-squared	0.93	0.03	0.129
D.V. Mean 01/2019-02/2020	0.93	0.03	3.61
<i>Panel D: Self-employed workers</i>			
COVINDEX	0.108*** (0.007)	-0.080*** (0.007)	0.060*** (0.007)
Observations	84,118	81,466	69,705
R-squared	0.051	0.036	0.099
D.V. Mean 01/2019-02/2020	0.92	0.05	3.57
<i>For all</i>			
Month FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2) to (3). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals currently employed. In column (3) we use those individuals in column (2) who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

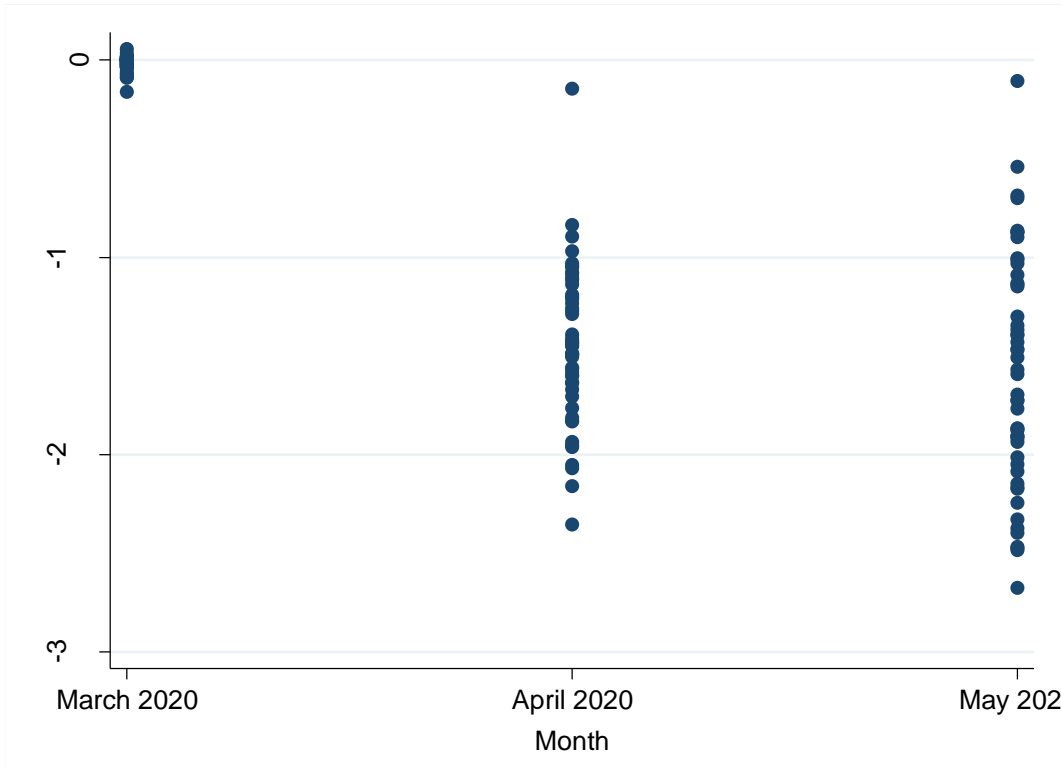
Appendix A: Summary statistics

Table A1: Summary Statistics

	01- 2019/02- 2020	March 2020	April 2020	May 2020	Diff (March 2020 and pre- COVID19)	Diff (April 2020 and pre- COVID19)	Diff (May 2020 and pre- COVID19)	Diff (May 2020 and April)
Public Sector								
% Employed (At work)	0.925	0.919	0.858	0.893	-0.006**	-0.067***	-0.032***	0.035***
% Employed (Did not work Last week)	0.046	0.051	0.053	0.033	0.005*	0.007**	-0.013***	-0.019***
% Unemployed	0.021	0.020	0.077	0.064	-0.001	0.056***	0.043***	-0.012***
% Out of labor force	0.008	0.011	0.012	0.009	0.003**	0.005***	0.001***	-0.004**
Mean work hours	38.700	38.605	38.168	38.343	-0.094	-0.532***	-0.357***	0.175
Private Sector								
% Employed (At work)	0.929	0.913	0.779	0.816	-0.016***	-0.150***	-0.114***	0.037***
% Employed (Did not work Last week)	0.026	0.031	0.054	0.039	0.006***	0.028***	0.014***	-0.014***
% Unemployed	0.036	0.046	0.148	0.129	0.010***	0.112***	0.093***	-0.019***
% Out of labor force	0.009	0.010	0.019	0.016	0.001*	0.010***	0.007***	-0.003***
Mean work hours	38.651	38.396	38.045	38.257	-0.255***	-0.606***	-0.394***	0.212**
Self-employed								
% Employed (At work)	0.922	0.896	0.739	0.796	-0.026***	-0.183***	-0.126***	0.058***
% Employed (Did not work Last week)	0.052	0.071	0.174	0.134	0.019***	0.122***	0.082***	-0.040***
% Unemployed	0.019	0.022	0.071	0.059	0.004	0.052***	0.040***	-0.012**
% Out of labor force	0.007	0.011	0.016	0.010	0.003**	0.009***	0.003**	-0.005**
Mean work hours	38.363	37.234	35.426	36.384	-1.129***	-2.937***	-1.979***	0.958***

Notes: Diff is measured as the employment outcomes for March, April, May, 2020 minus those in the pre-COVID period (01-2019/02-2020). *** indicates that the difference is statistically significant at the 1% level of significance, ** Significant at the 5% level, * Significant at the 10% level, based on a t-type test of equal means.

Figure A2: The COVINDEX over the post-COVID period (March, April, and May 2020)



Notes: This figure plots the values of the COVINDEX by month and state during the post-COVID period

Appendix B: Robustness Checks

Table B1: Robustness Check #1: Controlling for whether individuals were interviewed in person

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.046*** (0.004)	0.012*** (0.004)
Interview in person	0.004** (0.002)	0.009*** (0.003)
Observations	129,502	116,022
R-squared	0.041	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Both columns include a dummy variable that takes value 1 when the respondent was interviewed in person, and 0 otherwise. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B2: Robustness Check #2: Using a sample of individuals aged 16-64

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.047*** (0.004)	0.013*** (0.004)
Observations	130,003	116,318
R-squared	0.043	0.113
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B3: Robustness Check #3: Main results without trimming the extremes**(1)**

Dependent variable	Log (Work Hours Last Week)
COVINDEX	0.023*** (0.007)
Observations	118,812
R-squared	0.076
D.V. Mean 01/2019-02/2020	3.59
<i>For all</i>	
Month FE	Yes
State FE	Yes
Year FE	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old, who report being at work during the prior week. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation. Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample are individuals who report being at work during the prior week and who do not have more than one job from January 2019 to May 2020 Monthly CPS data. We show the robustness of our findings including individuals below the 1st percentile (working less than 5 hours in the public service) and above the 99th percentile (working more than 70 hours per week). Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B4: Robustness Check #4: Considering hours worked in all jobs and limiting the sample to individuals that do not spend time in second jobs

	(1)	(2)
Dependent variable	Log (Work Hours Last Week)	Log (Work Hours Last Week)
COVINDEX	0.016*** (0.004)	0.013*** (0.004)
Observations	115,451	108,485
R-squared	0.099	0.105
D.V. Mean 01/2019-02/2020	3.63	3.62
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old, who report being at work during the prior week. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation. Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample are individuals who report being at work during the prior week and who do not have more than one job from January 2019 to May 2020 Monthly CPS data. We show the robustness of our findings by considering hours worked in all jobs in column 1 and by limiting the sample to individuals that do not spend time in second jobs in column 2. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B5: Robustness Check #5: COVINDEX at county level

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.051*** (0.005)	0.013*** (0.004)
Observations	129,502	116,022
R-squared	0.041	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B6: Robustness Check #6: Including the date of the first death by state to gauge the COVINDEX

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.045*** (0.005)	0.014*** (0.005)
Deaths date Sub-INDEX	0.008 (0.016)	-0.006 (0.011)
Observations	129,502	116,022
R-squared	0.041	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B7: Robustness Check #7: Using the COVINDEX excluding mobility to parks

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.045*** (0.006)	0.009** (0.004)
Observations	129,502	116,022
R-squared	0.040	0.105
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table B8: Robustness Check #8: Adding/deleting occupation controls

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.046*** (0.004)	0.011*** (0.004)
Observations	129,502	116,022
R-squared	0.064	0.078
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (1). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Appendix C: Additional estimates

Table C1: Minimum mobility by category and employment outcomes

<i>Panel A: Retail and Recreation Mobility and employment outcomes (Public employees)</i>		
	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
Mobility	0.002*** (0.000)	0.0003*** (0.000)
Observations	129,502	116,022
R-squared	0.042	0.106
D.V. Mean 01/2019-02/2020	0.926	3.614
<i>Panel B: Grocery and Pharmacy Mobility and employment outcomes (Public employees)</i>		
Mobility	0.003*** (0.000)	0.001** (0.000)
Observations	129,502	116,022
R-squared	0.042	0.105
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>Panel C: Transit Stations Mobility and employment outcomes (Public employees)</i>		
Mobility	0.001*** (0.000)	0.0003** (0.000)
Observations	129,502	116,022
R-squared	0.041	0.105
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>Panel D: Workplaces Mobility and employment outcomes (Public employees)</i>		
Mobility	0.002*** (0.000)	0.0003** (0.000)
Observations	129,502	116,022
R-squared	0.041	0.105
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>Panel E: Parks Mobility and employment outcomes (Public employees)</i>		
Mobility	0.002*** (0.000)	0.0003** (0.000)
Observations	129,502	116,022
R-squared	0.041	0.105
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>Panel F: All mobility categories together (Public employees)</i>		
Average minimum drop in the mobility	0.002*** (0.000)	0.0004** (0.000)
Observations	129,502	116,022
R-squared	0.042	0.105
D.V. Mean 01/2019-02/2020	0.93	0.05

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table C2: Main results showing all coefficients incorporated in the specifications

	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.046*** (0.004)	0.013*** (0.004)
Age	0.011*** (0.001)	0.035*** (0.002)
Age2/100	-0.012*** (0.001)	-0.039*** (0.002)
Married	0.004 (0.003)	0.003 (0.004)
Male	0.030*** (0.002)	0.053*** (0.004)
Number of children	-0.011*** (0.003)	-0.009** (0.004)
High School	0.037*** (0.008)	0.072*** (0.017)
College	0.040*** (0.009)	0.056*** (0.016)
More college	0.050*** (0.010)	0.125*** (0.015)
Observations	129,502	116,022
R-squared	0.041	0.106
D.V. Mean 01/2019-02/2020	0.93	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample in column (2) are individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table C3: Predicting the Social Distancing Policy Adoption

Dependent variable:	Days between First COVID-19 Death and First SD Measure
	(1)
Panel A	
Share Employed	-4.368 (36.411)
Observations	51
R-squared	0.443
Region FE	Yes
Panel B	
Log (Mean Weekly Work Hours)	34.770 (25.643)
Observations	51
R-squared	0.467
Region FE	Yes

Notes: We estimate Equation (5). The proportion of employed individuals by state is calculated using a sample of civilian, not institutionalized individuals between 18 and 64 years old. We use individuals who report being at work during the prior week to construct the mean weekly work hours. All employment outcomes have been collapsed at the state level for the period January 2019 to February 2020. Fixed effects for the 9 US regions are included in all estimates (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific). Estimates are weighted. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Appendix D: Heterogeneous Analysis
Table D1: Heterogeneous Impacts by Gender

<i>Panel A: Public employees</i>				
	Males		Females	
	(1)	(2)	(3)	(4)
Dependent variable	Employed	Log (Work Hours Last Week)	Employed	Log (Work Hours Last Week)
COVINDEX	0.041*** (0.006)	0.015*** (0.005)	0.050*** (0.005)	0.012* (0.006)
Observations	54,163	49,098	75,339	66,924
R-squared	0.025	0.099	0.059	0.098
D.V. Mean 01/2019-02/2020	0.94	3.66	0.91	3.58
<i>Panel B: Private employees</i>				
COVINDEX	0.075*** (0.005)	0.017*** (0.003)	0.089*** (0.005)	0.015*** (0.002)
Observations	356,142	318,851	321,437	286,502
R-squared	0.039	0.121	0.040	0.103
D.V. Mean 01/2019-02/2020	0.93	3.66	0.92	3.55
<i>Panel C: Self-employed</i>				
COVINDEX	0.095*** (0.009)	0.057*** (0.007)	0.128*** (0.008)	0.065*** (0.012)
Observations	52,526	43,970	31,592	25,735
R-squared	0.047	0.066	0.059	0.056
D.V. Mean 01/2019-02/2020	0.93	3.65	0.91	3.43
<i>For all</i>				
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2), and (4). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in columns (1) and (3) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In column (2) and (4), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table D2: Heterogeneous Impacts by Race

<i>Panel A: Public employees</i>						
	White individuals		Black individuals		Other individuals	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Employed	Log (Work Hours Last Week)	Employed	Log (Work Hours Last Week)	Employed	Log (Work Hours Last Week)
COVINDEX	0.043*** (0.004)	0.012** (0.005)	0.053*** (0.012)	0.019** (0.008)	0.052*** (0.013)	0.007 (0.018)
Observations	102,648	91,922	15,508	14,034	11,346	10,066
R-squared	0.045	0.106	0.049	0.086	0.049	0.185
D.V. Mean 01/2019-02/2020	0.93	3.61	0.93	3.64	0.92	3.57
<i>Panel B: Private employees</i>						
COVINDEX	0.078*** (0.005)	0.017*** (0.002)	0.091*** (0.008)	0.016*** (0.005)	0.094*** (0.007)	0.012*** (0.005)
Observations	545,615	489,507	67,619	58,691	64,345	57,155
R-squared	0.035	0.134	0.048	0.112	0.056	0.134
D.V. Mean 01/2019-02/2020	0.93	3.61	0.90	3.60	0.93	3.60
<i>Panel C: Self-employed</i>						
COVINDEX	0.097*** (0.006)	0.058*** (0.007)	0.164*** (0.029)	0.050** (0.024)	0.144*** (0.016)	0.078*** (0.021)
Observations	72,486	60,331	4,922	3,956	6,710	5,418
R-squared	0.045	0.106	0.094	0.103	0.111	0.147
D.V. Mean 01/2019-02/2020	0.93	3.57	0.89	3.56	0.92	3.57
<i>For all</i>						
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2), (4), and (6). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in columns (1), (3), and (5) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In columns (2), (4), and (6), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table D3: Heterogeneous Impacts by Education

Panel A: Public employees				
	Some college or more		Less than college	
	(1)	(2)	(3)	(4)
Dependent variable	Employed	Log (Work Hours Last Week)	Employed	Log (Work Hours Last Week)
COVINDEX	0.038*** (0.004)	0.009* (0.005)	0.085*** (0.014)	0.030*** (0.008)
Observations	105,521	94,768	23,981	21,254
R-squared	0.041	0.090	0.048	0.116
D.V. Mean 01/2019-02/2020	0.93	3.62	0.92	3.58
Panel B: Private employees				
COVINDEX	0.068*** (0.004)	0.012*** (0.002)	0.110*** (0.006)	0.025*** (0.003)
Observations	433,222	390,996	244,357	214,357
R-squared	0.028	0.116	0.048	0.110
D.V. Mean 01/2019-02/2020	0.94	3.62	0.92	3.59
Panel C: Self-employed				
COVINDEX	0.101*** (0.009)	0.054*** (0.012)	0.122*** (0.009)	0.073*** (0.011)
Observations	56,234	46,966	27,884	22,739
R-squared	0.047	0.108	0.056	0.096
D.V. Mean 01/2019-02/2020	0.93	3.56	0.91	3.58
<i>For all</i>				
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2), and (4). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in columns (1) and (3) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In columns (2) and (4), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table D4: Main results depending on the type of job

<i>Panel A: Federal employee</i>		
	(1)	(2)
Dependent variable	Employed	Log (Work Hours Last Week)
COVINDEX	0.037*** (0.006)	0.005 (0.005)
Observations	25,595	23,372
R-squared	0.025	0.045
D.V. Mean 01/2019-02/2020	0.93	3.67
<i>Panel B: State employee</i>		
COVINDEX	0.034*** (0.008)	0.006 (0.008)
Observations	45,345	40,883
R-squared	0.041	0.158
D.V. Mean 01/2019-02/2020	0.93	3.59
<i>Panel C: Local employee</i>		
COVINDEX	0.057*** (0.005)	0.021*** (0.006)
Observations	58,562	51,767
R-squared	0.065	0.107
D.V. Mean 01/2019-02/2020	0.92	3.61
<i>For all</i>		
Month FE	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes public employees (current job or most recent job) between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, gender, marital status, parental status, and educational attainment. We also control for the type of occupation in column (2). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in Column (1) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In column (2), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table D5: Heterogeneous Impacts by the Essential vs. Non-essential Nature of the Job**Panel A: Public employees**

Dependent variable	Essential worker		Non-essential worker	
	(1)	(2)	(3)	(4)
	Employed	Log (Work Hours Last Week)	Employed	Log (Work Hours Last Week)
COVINDEX	0.028*** (0.004)	0.005* (0.003)	0.065*** (0.006)	0.024*** (0.007)
Observations	65,737	61,931	63,765	57,171
R-squared	0.013	0.050	0.097	0.099
D.V. Mean 01/2019-02/2020	0.95	3.65	0.91	3.57

Panel B: Private employees

COVINDEX	0.053*** (0.004)	0.013*** (0.002)	0.112*** (0.006)	0.021*** (0.003)
Observations	352,125	326,244	325,454	294,277
R-squared	0.021	0.070	0.060	0.117
D.V. Mean 01/2019-02/2020	0.93	3.62	0.92	3.59

Panel C: Self-employed

COVINDEX	0.083*** (0.010)	0.063*** (0.010)	0.122*** (0.007)	0.059*** (0.012)
Observations	31,842	29,063	52,276	47,066
R-squared	0.041	0.102	0.061	0.092
D.V. Mean 01/2019-02/2020	0.92	3.58	0.92	3.56

For all

Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2), and (4). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in columns (1) and (3) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In columns (2) and (4), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level

Table D6: Heterogeneous Impacts by industry and the Ability to Telework

Panel A: Public employees				
Dependent variable	Can telework		Cannot telework	
	(1)	(3) Log (Work Hours Last Week)	(4)	(6) Log (Work Hours Last Week)
COVINDEX x Health Care and Social Assistance	0.046*** (0.012)	-0.007 (0.011)	0.008 (0.008)	0.002 (0.010)
COVINDEX x Education	0.053*** (0.006)	0.029*** (0.009)	0.148*** (0.018)	0.093*** (0.013)
COVINDEX x Other industries	0.025*** (0.006)	-0.003 (0.006)	0.040*** (0.007)	-0.005 (0.006)
Observations	79,775	71,609	49,727	44,413
R-squared	0.064	0.102	0.038	0.132
D.V. Mean 01/2019-02/2020	0.92	3.61	0.93	3.62
Panel B: Private employees				
COVINDEX x Health Care and Social Assistance	0.070*** (0.006)	0.019*** (0.004)	0.046*** (0.006)	0.018*** (0.004)
COVINDEX x Education	0.070*** (0.008)	0.031*** (0.008)	0.132*** (0.018)	0.050*** (0.018)
COVINDEX x Other industries	0.038*** (0.004)	0.008*** (0.002)	0.126*** (0.006)	0.023*** (0.003)
Observations	268,845	246,221	408,734	359,132
R-squared	0.022	0.111	0.053	0.133
D.V. Mean 01/2019-02/2020	0.94	3.65	0.92	3.58
Panel C: Self-employed				
COVINDEX x Health Care and Social Assistance	0.075*** (0.019)	0.042 (0.033)	0.099*** (0.022)	0.129*** (0.028)
COVINDEX x Education	0.128*** (0.028)	0.103** (0.046)	0.196* (0.102)	0.205 (0.138)
COVINDEX x Other industries	0.080*** (0.010)	0.048*** (0.013)	0.133*** (0.009)	0.061*** (0.010)
Observations	37,214	31,490	46,904	38,215
R-squared	0.038	0.118	0.064	0.096
D.V. Mean 01/2019-02/2020	0.93	3.57	0.92	3.57
<i>For all</i>				
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes individuals between 18 and 64 years old. We estimate Equation (3). All regressions include a constant, as well as demographic controls for age, marital status, parental status, and educational attainment. We also control for the type of occupation in columns (2), and (4). Please refer to table E1 in the Data Appendix for a detailed description of each variable. The sample in columns (1) and (3) is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. In columns (2) and (4), we use those individuals who report being at work during the prior week. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Data Appendix
Table E1: Sum stats and definitions of CPS variables

Name	CPS variable	Definition	Mean	S.D.
A. Individual characteristics				
Age	AGE gives each person's age at last birthday	Years	42.97	12.17
Children	NCHILD counts the number of own children (of any age or marital status) residing with each individual. NCHILD includes step-children and adopted children as well as biological children. Persons with no children present are coded 0.	Dummy variable equal to 1 if NCHILD>0	0.49	0.50
High school	EDUC indicates respondents' educational attainment, as measured by the highest year of school or degree completed. Note that completion differs from the highest year of school attendance; for example, respondents who attended 10th grade but did not finish were classified in EDUC as having completed 9th grade. Values of this variable:	Dummy variable equal to 1 if EDUC==73	0.16	0.37
College	None or preschool	2	0.25	0.43
	Grades 1, 2, 3, or 4	10		
	Grades 5 or 6	20		
	Grades 7 or 8	30		
	Grade 9	40		
	Grade 10	50		
	Grade 11	60		
	12th grade, no diploma	71		
	High school diploma or equivalent	73		
	Some college but no degree	81		
More college	Associate's degree, occupational/vocational	91	0.56	0.50
	Associate's degree, academic program	92		
	Bachelor's degree	111		
	Master's degree	123		
	Professional school degree	124		
	Doctorate degree	125		
Male	SEX gives each person's sex. Values of this variable: Male Female	Dummy variable equal to 1 if SEX==1 1 2	0.42	0.49
Married	MARST gives each person's current marital status, including whether the spouse was currently living in the same household. Values of this variable: Married, spouse present Married, spouse absent Separated Divorced	Dummy variable equal to 1 if MARST==1 or MARST==2 1 2 3 4	0.60	0.49

	Widowed	5			
	Never married/single	6			
B. Employment Outcomes					
Employed	EMPSTAT indicates whether persons were part of the labor force--working or seeking work--and, if so, whether they were currently unemployed. The variable also provides information on the activity (e.g., doing housework, attending school,) or status (e.g., retired, unable to work) of persons not in the labor force, as well as limited additional information on those who are in the labor force (e.g. members of the Armed Forces, those with a job, but not at work last week). Values of this variable:		Dummy variable equal to 1 if EMPSTAT=10 at work	0.92	0.27
	At work	10			
	Has job, not at work last week	12			
	Unemployed, experienced worker	21			
	Unemployed, new worker	22			
	NILF, unable to work	32			
	NILF, other	34			
	NILF, retired	36			
Did not Work Last Week	See EMPSTAT above. We limit the sample to employed individuals		Dummy variable equal to 1 if EMPSTAT=12 has job but did not work last week	0.05	0.21
Log (Work Hours Last Week)	AHRSWORK1 is the actual number of hours the respondent reported working at his/her main job last week. The universe is Civilians age 15+ who are employed and either at work and were at work during the survey week.		Logarithm of hours worked last week	3.56	0.45

Table E2: Description of the NPIs

NPIs	Definition	Closure Data Source	Reopening Data Source
Emergency Declaration	Emergency declaration; currently includes State of Emergency, Public Health Emergency, and Public Health Disaster declarations.	Fullman et al., (2020) and National Governors Association (NGA)	National Governors Association (NGA), The New York Times and Coronavirus Resource Center
School Closure	Formal closing of schools.	Fullman et al., (2020), National Governors Association (NGA) and Education Week	National Governors Association (NGA), The New York Times and Coronavirus Resource Center
Partial Business Close	Partial business closures incorporate partial closures without specifying the closures of non-essential business such as restriction or limitation of restaurants, casinos, gyms, fitness centers and entertainment venues among others.	Fullman et al., (2020) and National Governors Association (NGA)	National Governors Association (NGA), The New York Times and Coronavirus Resource Center
Non-essential Business Close	Mandate to close all non-essential businesses. Coding a case as a closure order requires the executive order to use phrasing indicative of a mandate (e.g., "non-essential businesses are required to close", "non-essential businesses must cease operations by date").	Fullman et al., (2020) and National Governors Association (NGA)	National Governors Association (NGA), The New York Times and Coronavirus Resource Center
Stay-at-home Order	Mandate for individuals to stay-at-home for all non-essential activities. Shelter-in-place and stay-at-home orders are considered to be equivalent.	Fullman et al., (2020) and National Governors Association (NGA)	National Governors Association (NGA), The New York Times and Coronavirus Resource Center