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Effect of a Federal Paid Sick Leave Mandate on Working and Staying at Home: Evidence from Cellular Device Data
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ABSTRACT

We study the effects of the temporary federal paid sick leave mandate that became effective April 1st, 2020 on ‘social distancing,’ as proxied by physical mobility behavior gleaned from cellular devices. The national paid leave policy was implemented in response to the COVID-19 outbreak and provided many private and many public employees, including individuals employed in the gig economy, with up to two weeks of paid leave. We study the early impact of the federal paid sick leave policy using interrupted time series analyses and difference-in-differences methods leveraging pre-FFCRA county-level differences in mobility. Our proxies for the ability to social distance are the share of cellular devices that are located in the workplace eight or more hours per day (‘full-time work’) and leave the home for less than one hour per day (‘at home’) in each county. Our findings suggest that the federal mandate decreased our full-time work proxy and increased our at home proxy. In particular, we find an initial decrease in working full-time of 17.7% and increase in staying home of 7.5%, with effects dissipating within three weeks. Given that up to 47% of employees are covered by the federal mandate, our effect sizes are arguably non-trivial.

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1. Introduction

As of May 6th, 2020 there were nearly 3.6 million confirmed global cases of the novel coronavirus 2019 (COVID-19) and more than 248,000 deaths (World Health Organization 2020b). COVID-19 is a viral disease caused by infection with the virus SARS-CoV-2. Infected individuals are contagious for a period of up to 14 days and before displaying symptoms (e.g., dry cough and fever). The virus can survive on surfaces for up to 72 hours. COVID-19 is highly infectious with an estimated reproduction number – the number of people a sick person will infect – of 2.24 to 3.58 (Zhang et al. 2020; Zhao et al. 2020). The virus spreads from person-to-person during close (i.e., one meter) physical interactions due to droplets of fluid from coughing, sneezing, and/or talking (World Health Organization 2020d).

Currently, there is no cure or vaccine for COVID-19.[1] Thus, public health measures are the primary means to mitigate disease spread. The World Health Organization suggests that individuals exposed to COVID-19 self-isolate for 14 days and all people (symptomatic and non-symptomatic) practice social distancing. A study using Israeli data collected in the lead-up to the COVID-19 outbreak shows that 97% of adults report that they would comply with a government mandate to self-quarantine if their wages were compensated, but compliance falls to 57% without compensation (Bodas and Peleg 2020), suggesting the importance of financial protection for effective social distancing. The U.S. does not have a universal, national paid sick leave (PSL) policy. Thus, how effectively the U.S may be able to advance a meaningful mitigation strategy based on social distancing is unclear. Working while sick is common in the U.S.:

[1] At the time of writing, there are ongoing clinical trials for potential vaccines and therapies. See for example, the World Health Organization (2020c) listing of potential vaccines. Preliminary data suggests that the drug Remdesivir may reduce mortality risk and time to recovery (National Institutes of Health 2020). On May 1st, 2020, the Food and Drug Agency approved Remdesivir to treat hospitalized COVID-19 patients (https://www.fda.gov/media/137564/download; last accessed May 5th, 2020).

survey data suggest that 90% of employees report coming to work while sick (Accountemps 2019), possibly due to fear of income or job loss.

In response to the surge in COVID-19 cases and deaths, the U.S. federal government adopted a *temporary* national PSL policy: the Families First Coronavirus Response Act on March 18th, 2020 (FFCRA) (116th Congress of the United States 2020). This Act, which became effective April 1st, 2020 and will sunset at the end of 2020, compels many private and public employers to offer up to two weeks of temporary emergency sick leave to employees for COVID-19-related treatment, isolation, childcare due to school/daycare closures, and/or care for dependents impacted by COVID-19. Individuals working in the gig economy are also eligible for FFCRA benefits. The objective of this Act is to provide financial support to those with COVID-19 and/or caring for children/dependents during the pandemic, and ultimately reduce disease spread within the population.

We provide the first evidence on the impact of the federal FFCRA on 'physical mobility'—a proxy for social-distancing, measured using GPS tracking of cellular devices. Specifically, we consider proxies for being at a workplace full-time and staying home. We estimate the early effect of FFCRA using interrupted time series analyses and difference-in-differences methods that leverage heterogeneity in treatment intensity based on pre-FFCRA physical mobility.

2. Related literature

2.1. Paid sick leave mandate effects

Several studies examine the effect of PSL mandates on labor outcomes. Many of the early studies focus on Europe, where mandates have been in place for longer relative to newer state and local mandates in the U.S. Mandated PSL generosity in Sweden and Italy increases work absences (Henrekson and Persson 2004; Scognamiglio 2019). Puhani and Sonderhof

(2010), Ziebarth and Karlsson (2010), and Ziebarth and Karlsson (2014) investigate German legislation that decreased sick pay from 100% to 80% of wages for two years, and then reinstated wages to 100%. Sick days decreased by 2.4 days during the two-year period in which PSL benefits were less generous (Puhani and Sonderhof 2010), and 6% to 8% more employees reported taking no days off during this time (Ziebarth and Karlsson 2010).

In the U.S., studies find that PSL mandates increase PSL coverage, especially for employees in industries historically lacking benefits (Maclean, Pichler, and Ziebarth 2020; Callison and Pesko 2020). These mandates do not reduce employment, wages, or non-mandated benefits (Maclean, Pichler, and Ziebarth 2020; Pichler and Ziebarth 2020). However, PSL mandates increase workplace absences overall (Maclean, Pichler, and Ziebarth 2020; Callison and Pesko 2020; Schneider 2020; Colla et al. 2014; Ahn and Yelowitz 2016), and several studies are able to evaluate heterogeneity in which types of workplace absences increase post-mandate. Stearns and White (2018) find that PSL mandates adopted in Connecticut and Washington, DC increase illness-related work absences, but do not increase work absences for non-illness reasons (e.g., childcare). Callison and Pesko (2020) do not find evidence that PSL mandates increase work absences nationally for own illness, but the authors document increases in leave-taking for a broader group of absences including child care problems or other personal/family obligations, and these effects were disproportionately higher for households with children. One possible explanation is that PSL mandates are used to care for a sick child. Additionally, Callison and Pesko (2020) find evidence that PSL mandates reduce presenteeism (i.e., working while sick) by 4.5 ppts. Similarly, a study shows that the Washington state PSL mandate reduces presenteeism by eight ppts for employees in the retail and food service industries (Schneider 2020).

A few studies examine the effect of PSL mandates on measures of health or healthcare utilization. The temporary decrease in the generosity of German PSL mandate reduced hospitalizations and hospital visits but had no effect on self-reported health (Puhani and Sonderhof 2010). Similarly, restoring the PSL mandate generosity had no effect on self-reported health satisfaction (Ziebarth and Karlsson 2014). Pichler and Ziebarth (2017) use high-frequency Google influenza data in the U.S. to show that population-level influenza-like disease rates (as measured by searches related to the illness or its symptoms) decrease after employees gain access to PSL following mandate adoption, suggesting PSL mandates have positive spillover effects by preventing the disease spread. In a follow-up study using administrative data on physician-certified influenza, Pichler, Wen, and Ziebarth (2020) confirm this finding.

2.2. Analyses of COVID-19 and associated policies

There is an emerging economic literature evaluating effects of the COVID-19 pandemic and associated policies on economic and health outcomes. We mention a few studies that investigate the effect of the COVID-19 pandemic and legislation this virus has precipitated on social distancing behaviors. One study finds that the lockdown of Wuhan, China (the city in which the virus was first identified) reduced inflow into, out of and with Wuhan (Fang, Wang, and Yang 2020), thus reducing infections outside of Wuhan. Another study using Chinese data finds that mandatory, but not voluntary, social distancing is effective at flattening the pandemic curve (Chudik, Pesaran, and Rebucci 2020).

A U.S. study uses aggregate human mobility and location trends published by Google for the month of March 2020 to explore the effect of six different types of orders: statewide stay-at-home order, other stay home orders, non-essential business closure, large gatherings ban, school closure, and restaurant/bar limits (Abouk and Heydari 2020). State-wide stay-at-home orders appear to have the largest effect on reducing mobility.

Several studies use SafeGraph data to assess the impact of social distancing policies. Higher income and high-speed internet predict people's ability to obey social distancing directives (Chiou and Tucker 2020). People living in areas with more Republicans engage in less social distancing behaviors that residents in other areas (Allcott et al. 2020; Andersen 2020). Gupta et al. (2020) estimate that a state or county policy change or informational event each reduces mobility by 2% to 8%, with policies of a more information nature explaining in total up to half of the declines in mobility experienced from early March to early April 2020.

Friedson et al. (2020) show that California's stay-at-home order – the first such policy in the U.S. during the COVID-19 pandemic – was effective in encouraging people to remain in their homes. The policy also reduced both COVID-19 cases and deaths, but lead to job losses. Early stay-at-home orders and those adopted in high population-density localities appear to be the most impactful (Dave et al. 2020). Finally, Courtemanche et al. (2020) use administrative data to show that Kentucky's stay-at-home order reduced the number of confirmed cases in that state relative to other Southern and Midwest states.

3. U.S. paid sick leave and policies

3.1. Paid sick leave coverage in the U.S., and state and local paid sick leave mandates

Providing PSL benefits largely been left to employers in the U.S. In March 2019, 76% of civilian employees had access to PSL through their employer, ranging from 73% among private employees to 91% of government employees (Bureau of Labor Statistics 2020a). The average number of PSL days available to employees was eight days per year in 2019 (Bureau of Labor

Statistics 2020b), thus less than the recommended 14 days of self-quarantine recommended following exposure to an individual infected with COVID-19.

These averages conceal substantial heterogeneity in access to PSL (see Appendix Table 1; based on tabulations listed in Bureau of Labor Statistics (2020a)). The PSL coverage rate is 94% among employees in management, business, and financial occupations while the rate is 59% among employees in construction, extraction, farming, fishing, and forestry occupations. 86% of full-time employees have access to PSL and 43% of part time employees have access, and coverage rates are 94% among the highest 10% of wage earners and 31% among the lowest 10% of wage earners. The coverage rate among large employers (more than 500 employees) is 91% while the coverage rate is 64% among small employers (less than 50 employees).[2]

The general pattern that emerges from Appendix Table 1 is that employees in 'good jobs' – i.e., more prestigious, full-time, and higher wage jobs at larger employers– are substantially more likely to have access to PSL than other employees. As documented by Maclean, Pichler, and Ziebarth (2020), coverage rates are particularly low in the food preparation and serving occupations (25%), and retail trade (53%) and accommodation and food services (27%) industries, which is troubling for disease spread given the substantial face-to-face contact between employees and clients involved in such jobs.[3] Further, many of these jobs are likely deemed 'essential work' by the U.S. federal government during the COVID-19 outbreak, and thus such individuals are required under the Defense Production Act to work.

Beginning with San Francisco, California in February 2007, 34 localities have passed mandates to expand access to PSL among employees, see Appendix Table 2 (A Better Balance

[2] Using data from the National Health Interview Survey (NHIS), Callison and Pesko (2020) find below the mean PSL coverage rates for employees in the agriculture/forestry/fishing, construction, arts/entertainment, and accommodation/food services industries.
[3] We note that Maclean and colleagues only focus on private employees, the target group for PSL mandates.

2020). Eleven of the mandates are at the state-level. All PSL policies are employer mandates. While the specifics vary across PSL mandate, in general the mandates to date require employees to work for a specified period of time with the employer before gaining eligibility to the benefit. Most mandates compel private employers to provide approximately seven days of PSL annually, unused days can be rolled over to the next calendar year. There are exemptions to PSL mandates. Small employers are often exempt from these mandates and some mandates exclude entire industries. Of note, the benefits conferred by state and local PSL mandates -- up to seven days (A Better Balance 2020) -- are likely not sufficient to allow for effective isolation in the context of COVID-19. Further, many employees may not have worked at their employer long enough to have accrued a meaningful amount of PSL

3.2. FFCRA

FFCRA compels certain private employers with less than 500 employees and some public employers to offer temporary paid leave to all employees (Federal Resgister 2020). FFCRA applies to the gig economy (e.g., Uber) but exempts many small businesses with fewer than 50 employees. Qualifying reasons for PSL include: (i) employee is subject to a Federal, state, or local quarantine or isolation order; (ii) a healthcare professional has recommended that the employee self-quarantine; (iii) the employee is experiencing COVID-19 symptoms or similar symptoms and is currently seeking a diagnosis from a healthcare professional; (iv) the employee is caring for an individual(s) subject to (i) or (ii); and (v) the employee is caring for a child whose school or daycare is closed, or whose childcare provider is not available for reasons related to COVID-19. Estimates suggest that FFCRA will cover 17% to 47% of U.S. employees (Glynn 2020). FFCRA's low coverage rate is believed to be attributable to the large number of exemptions (e.g., exempting employers with over 500 employees).

FFCRA provides eligible employees who are unable to work because they are in quarantine or are experiencing COVID-19 symptoms and seeking a diagnosis with two weeks (up to a maximum of 80 hours) of PSL at the employee's regular rate of pay or the applicable minimum wage (whichever is higher), up to a maximum of $511 per day. Employees who are caring for children whose schools/daycares have closed due to COVID-19 or who are tending to dependents with COVID-19 are eligible for two weeks (up to a maximum of 80 hours) of PSL at two-thirds of the employee's regular rate of pay, or the applicable minimum wage, up to $200 per day. Employers initially pay the benefits, but later receive federal reimbursable tax credits (Internal Revenue Service 2020). Unlike state and local PSLs, there is no accrual period for FFCRA benefits.

Additional benefits are available to some employees who have worked for the employer for more than 30 days under The Emergency Family and Medical Leave Expansion Act (EFMLEA), which extends Title I of the Family and Medical Leave Act, an Act that provides *unpaid* leave to qualifying employees. Such employees are eligible for an additional ten weeks of paid expanded family and medical leave at two-thirds the employee's regular rate of pay if the employee is not able to work due to COVID-19 symptoms and/or must care for a child whose school or daycare is closed, or childcare provider is not available.[4]

Thus, FFCRA is arguably more generous, in terms of covered employees and benefits, than state and local PSLMs described in Section 3.2. However, the Act is temporary, is limited to COVID-19 sickness and responsibilities, arguably affects different employees and employers than the PSL mandates, and is implemented during a global pandemic. Thus, the extent to which we can extrapolate from previous PSL work to FFCRA is unclear.

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[4] Interested readers can see the Department of Labor for more details on FFCRA: https://www.dol.gov/agencies/whd/pandemic/ffcra-employee-paid-leave (last accessed May 5th, 2020).

4. Data, outcome variables, and methods

4.1. SafeGraph Inc.

We use aggregated, high frequency geolocation data from SafeGraph Inc. (a company that aggregates anonymized location data from numerous cellular applications) covering the period covering March 25th, 2020 through April 24th, 2020 on a daily basis.[5] We exclude earlier days in March given that multiple policies were adopted and numerous pieces of information related to COVID-19 became available during this period. SafeGraph data cover over 20 million cellular devices and are freely available to researchers. These data allow us to accurately locate individual cellular devices and track the share of devices that leave the home area in real-time, and are therefore ideal for our study. SafeGraph identifies locations for a device using a GeoHash-7 encoding algorithm that covers the globe with a grid that is approximately 500 feet per side. Devices are included in the sample if SafeGraph can identify a home location for the device, which requires a device to be on and consistently present at a location during nighttime hours for a six week period. Because SafeGraph data are based on users of cellular applications who have opted in to location sharing, the number of devices in the sample changes over time. Given our short study period and the above-noted six week requirement, we do not expect that the sample of cellular devices to be a function of FFCRA implementation.

SafeGraph excludes census block group information with fewer than five active devices on a given day. We aggregate the number of active devices in each county and the number of devices that stayed at home or visited a single location for three or more hours during regular business hours, from census block groups to the relevant county. To isolate FFCRA effects, we use counties that were not covered by a PSL mandate prior to FFCRA (A Better Balance 2020).

[5] Please see www.safegraph.com (last accessed May 5th, 2020).

Appendix Table 2 lists localities with a pre-FFCRA PSL mandate. The study sample includes 2,770 counties and county equivalents out of a total of 3,143 in the country; we do not differentiate between counties and equivalents. We observe each county in each of the 25 days in our study period, thus the sample is balanced, but we exclude weekends.

4.2. Outcomes

We consider two physical mobility outcomes. The measures we consider are based on movement of *cellular devices* within U.S. counties and may therefore not fully reflect physical mobility patterns of *individuals*.[6] First, we consider a proxy for working full-time: the share of cellular devices that are located in the likely place of work for six or more hours per day, where a work location is identified by movement patterns between 9 AM and 5 PM on weekdays. We note that this measure may include time spent at school for some individuals.[7] Second, we examine a proxy for staying in the home: the share of cellular devices that are located outside the home (as determined by SafeGraph's methodology described in Section 4.1) less than one hour per day. We acknowledge that our measures are somewhat arbitrary and there is, to the best of our knowledge, no standard set of measures given the newness of cellular device based location data to the research community.

4.3. Methods

As FFCRA applies to the entire U.S., our primary empirical approach is an interrupted time series analysis (ITSA). Equation (1) outlines our main empirical model:

$$(1) \qquad Y_{c,s,t} = \alpha_0 + \alpha_1 FFCRA_t + \alpha_2 T_t + \alpha_3 FFCRA_t * T_t + P_{s,t}\alpha_4 + \delta_c + \theta_t + \varepsilon_{c,s,t}$$

[6] For example, if an individual did not take their cellular device with them when they left their home for work, then we would not capture this working behavior and instead we would, erroneously, code this individual as at home. However, we cannot envision any reason why the propensity to carry a cellular device, vs. leaving the device at home, should be correlated with FFCRA implementation.

[7] Individuals must be 13 years or older to be included in the SafeGraph sample. Thus, elementary and middle school students are not included in the sample, but high school and college students may be included. For this latter group of students, we acknowledge that we may classify being at school as being at work using our variable definition.

Where $Y_{c,s,t}$ is a measure of physical mobility in county c in in day t. $FFCRA_t$ is an indicator variable taking on the value of one April 1st, 2020 onward and zero otherwise. T_t is a linear time trend. $P_{s,t}$ is a vector of state-level social distancing policies prompted by the COVID-19 pandemic: i.e., public school closure, stay-at-home order, and prohibition on in-restaurant dining (Raifman 2020).[8] δ_c is a vector of county fixed-effects that control for time-invariant characteristics of each county. $\varepsilon_{c,s,t}$ is the error term.

The parameters of central interest in our study are: α_1 which captures any immediate change in physical mobility that occurred when FFCRA became effective on April 1st, 2020; α_2 which captures the pre-FFCRA trend in physical mobility, and α_3 reflects the post-FFCRA trend in physical mobility. The identifying assumption in our ITSA model is that we are able to accurately capture the counterfactual trend in our outcomes that would have prevailed absent FFCRA using our parametric function of time.

We also estimate a non-parametric event-study-style model in the spirit of Autor (2003) and Kuehnle (2019). We include leads and lags around FFCRA. Our non-parametric event-study regression is outlined in Equation (2):

$$(2) \qquad Y_{c,s,t} = \beta_0 + \sum_{j=1}^{J} \gamma_j Rel\_time_j + P_{s,t}\beta_1 + \delta_c + \mu_{c,s,t}$$

Where γ_j measures the difference in $Y_{c,s,t}$ relative to the level in the county on March 31st, 2020. The non-parametric event-study model also controls for state-level policies and county fixed-effects.

[8] Results, available on request, are robust to using the coding scheme outlined in Fullman et al. (2020).

As a secondary specification,[9] we estimate a bite-style model (Alpert, Powell, and Pacula 2018; Courtemanche et al. 2017; Powell and Pacula 2020), this model is a modification of standard difference-in-differences which leverages variation in treatment intensity that is attributable to differences in pre-treatment characteristics across localities. The motivation for this specification is that we should observe a larger effects of FFCRA in terms of working full-time and staying home, in areas which at baseline had high degrees of full-time work pre-FFCRA, so there is likely to be more 'bite' in such counties.

In particular, we interact the $FFCRA_t$ with the share of devices that exhibited weekday full-time work in February of 2020. We construct our pre-period mobility measure using data from February since the extent of the COVID-19 outbreak was unclear at that time and there is little evidence that people began altering their behavior prior to February 29th, 2020 when the first death in the U.S. was reported (Centers for Disease Control and Prevention 2020). The regression model for our bite design model is outlined in Equation (3):

$$(3) \qquad Y_{c,s,t} = \pi_0 + \pi_1 FFCRA_t * Bite_{c,s} + P_{s,t}\pi_2 + D_{c,s,t}\pi_3 + \delta_c + \theta_t + \eta_{c,s,t}$$

Where $Bite_{c,s}$ is the fraction of devices working full-time in February of 2020 in county c and δ_c and θ_t are county and date fixed-effects, respectively. Because of the substantial disruptions in activity during the middle of March, as the scope of the pandemic became apparent and states were implementing various social distancing measures, we exclude data from March when estimating Equation (3). In Equation (3), the coefficient of interest is π_1, with larger values of π_1 indicating that more devices in a county exhibited a given behavior after the FFCRA took effect in counties that had a greater share of devices exhibiting working behavior.

[9] We use the bite design as secondary specification given seasonality in our outcomes. Put differently, as we outline in this section, we define our 'bite' measures using data from early February 2020. As carefully described in Gupta et al. (2020), there are differences in the propensity to travel in early February and late March/April. For this reason, we use ITSA as our primary specification and the bite design as our secondary specification.

We estimate least squares regression. The data are weighted by the county population. The appropriate level at which to cluster standard errors is not immediately clear. In our main analysis, we cluster standard errors at the county level. However, we show that results are similar using other inference approaches in Section 5.7.[10]

5. Results

5.1. Summary statistics and trends

Appendix Figure 1 reports cumulative cases and deaths over the study period, both trends increase sharply over this time period. Table 1 provides summary statistics in the pre-FFCRA period. In each county, 17.5% of devices exhibited workweek full-timework and 41.3% were at home. Demeaned trends for our physical mobility outcomes are reported in Figure 1 (we use the grand mean over the full study period). Over the study period the share of devices at work full-time declined while the share of devices at home increased. This pattern of results is in line with trends over the pandemic (see Section 2.2). As policies were adopted and information regarding COVID-19 emerged, Americans were more likely to practice social distancing.

5.2. Effect of FFCRA on physical mobility measures

Results based on our baseline specification are reported in Table 2 (Panel A). We observe an initial decrease in full-time work of 2.2 ppts or 17.7% relative to the baseline, which is 12.4% and measured over the period March 25th to March 31st. We compare all absolute effects to this benchmark when converting to relative effect sizes. However, we note that the actual effects may be larger than implied by our calculations using the period between March 25th and 31st as our estimated effects are likely driven by individuals who did not have access to

[10] To be conservative, we only list coefficient estimates as statistically different from zero at the 5% level or better.

PSL prior to FFCRA.[11] As observed in Figure 1, full-time work was declining prior to April 1st (-0.1 ppts or 0.8% per day). In addition to the immediate level shift at the time of policy adoption that we document, post-FFCRA there is a change in trend. The observed decline in full-time work is moderated as indicated by the positive coefficient estimate on the interaction between FFCRA and time. Combining the level shift and change in trend suggests that the impact of FFCRA on working full-time dissipates as time passes. Our coefficient estimates imply that the decrease in full-time work disappears after 22 days. This pattern of results is not surprising as FFCRA provides two weeks of paid sick leave for most employees with only some employees eligible for extended leave through the policy.

Our findings for staying home largely mirror those for full-time work. At the time of FFCRA adoption, the share of cellular devices exhibiting staying at home behavior increased by 4.2 ppts (or 7.5%). Over our study period, the share of devices at home was increasing in the pre-FFCRA period by 0.3 ppts (0.5%) per day, although this trend fell post-FFCRA as indicated by the positive coefficient estimate on the interaction between FFCRA and the post-period time trend. Staying home effects dissipate after eight and a half days.

During the period covered by our study, states were active in implementing social distancing policies. While there is no other policy that occurred nationwide on April 1st, 2020 that might confound out effects, we next test whether controlling for state social distancing policies might affect our results. We find that state-level social distancing policies decrease time at work and increase time at home. We document that public school closures, stay-at-home

[11] Or individuals with access to PSL benefits prior to FFCRA may have used up some of their benefits as COVID-19 emerged (in most areas) in the U.S. following two months in which influenza is common (January and February). Influenza is a common reason for using PSL.

orders, and prohibiting in-restaurant dining promote social distancing. We do not observe any evidence that non-essential business closures are important determinants of our outcomes.[12]

5.3. Internal validity

We next estimate a non-parametric event-study-style model to visually examine how the outcome variable develops over time (condition on control variables) in relation to ITSA. Figure 2 reports report the event-studies graphically. While full-time work appears to provide evidence of little movement in the week leading up to FFCRA, we find staying at home appears to increase in the two days before policy adoption. This pattern of results is arguably not unexpected given that there were many changes (economic, information, policy, and social) ongoing during the pre-treatment period. Further, FFCRA may have acted as a 'signal' to some individuals, prompting them to remain home and practice social distancing. This Act was signed on March 18th, 2020 which itself could have also conveyed information to individuals. The pre-trends do not display a clear pattern and, reassuringly, the policy lags demonstrate that the broad patterns we estimate in the ITSA hold: declining full-time work and increasing time at home.

5.4. Effect of FFCRA on physical mobility measures: 'Bite' design

We next report results using a modified difference-in-differences method that exploits the intensity of a national policy based on county-level February weekday full-time work, which we refer to as a 'bite' design (as described in Section 4.3). Results are reported in Table 2 Panel B. As expected, counties with higher shares of working full-time (as designated based on cell device data) display larger declines in full-time work but larger increases in the staying at home post-FFCRA. We view these results as confirming our ITSA findings.

[12] We observe no clear pattern of results from interactions between FFCRA and social distancing policies (not reported but available on request), suggesting no conclusive evidence on whether FFCRA enhanced the effectiveness of these policies.

5.5. Interactions between FFCRA and pre-FFCRA PSL mandates

As discussed in Section 2.1., 34 localities across the country had a PSL mandate in place prior to FFCRA. We exclude counties covered by a pre-FFCRA PSL mandate in our main analysis. While the benefits conferred by FFCRA arguably differ from those made available by the PSL mandates, we hypothesize that localities with a PSL mandate in place prior to FFCRA may have been better able to support the effective implementation of the federal Act. We test this hypothesis by interaction the FFCRA indicator with an indicator for a county with a PSL mandate in place prior to April 1st, 2020. Our hypothesis is based on the assumption that both employers and employees in counties with a pre-FFCRA PSL mandate are more supportive of such a benefit (e.g., taking paid leave is more socially acceptable, employers are more aware of such benefits and thus better able to communicate PSL conferred by FFCRA to employees).

To test this hypothesis, we include counties with a PSL mandate in the analysis sample. Results, reported in Table 3, support our hypothesis. More specifically, the interaction term in the full-time work (staying home) specification is negative (positive), which implies that FFCRA effects are enhanced by prior PSL mandates.

5.6. Heterogeneity in FFCRA effects across race, industry, and education

While COVID-19 has affected all of the U.S., particular groups have been especially hard-hit., e.g., rates of cases and deaths have been very high among African Americans (Villarosa 2020). Similarly, as documented in Appendix Table 1, employees in less desirable jobs are less likely to have access to PSL through their employer, we therefore expect FFCRA effects to be larger among this group of workers.

To explore hypotheses related to disparate impacts, we interact the FFCRA with the share of the county that is African American, other race, Hispanic, works in a blue collar occupation,[13] and has a college degree (the final variable offers a proxy for employees in jobs likely to provide PSL) using data from the 2014 to 2018 American Community Survey.[14,15] Results are reported in Table 4. Higher shares of African American offset FFCRA effects for full-time work. Interestingly, higher shares of Hispanics *increase* FFCRA effects of staying home. As expected, FFCRA effects for full-time work are larger in counties with higher shares of blue collar employees. This effect, however, is not mirrored in the at home results. Finally, and counter to our expectation, full-time work effects are *greater* in counties characterized by higher shares of college educated individuals. We hypothesize that such counties, through a more educated population, may be better able to absorb new health information (Grossman 1972).

5.7. Robustness

We conduct a number of robustness checks to assess the stability of our findings across alternative specifications and samples. Our results are not appreciably changed across these checks, thus we simply summarize our analyses.

First, more flexibly model the interactions between FFCRA and time, post-Act. In particular, we include a quadratic in time and interact the quadratic with the FFCRA indicator (Appendix Table 3). This specification arguably allows us to control for the changing policy and information environment in the U.S. as a whole over the pandemic. Second, we include a dummy variable for the two-week post-FFRCA period to control for the fact that most benefits

[13] We use the following occupations as blue collar: service; sales; office and administration support; farming, fishing, and forestry; construction and extraction; installation maintenance and repair; production; and transportation and material moving.
[14] We de-mean the county shares for ease of interpretation.
[15] Data available through https://nhgis.org/ (last accessed May 5th, 2020).

conferred by this federal Act last just two weeks (Appendix Table 4).[16] Third, we remove population weights and estimate unweighted regressions (Appendix Table 5).

Fourth, we change the control variables we include in Equation (1): (i) exclude state-level social distancing policies (Appendix Table 6) and (ii) include 'information' controls – the first confirmed case and death in the county (Johns Hopkins University Coronavirus Resource Center 2020), and the first death in the state (Appendix Table 7). We cannot include the first confirmed case in the state as all states had a confirmed case by March 25th, 2020. Fifth, we extend our pre-treatment period to February 2nd, 2020 -- the first day for which we have SafeGraph data (Appendix Table 8).

Sixth, we use alternative proxies for full-time work (away from home for ten hours or more) and staying home (away from home for less than two hours), see Appendix Table 9. Seventh, we include counties with a PSL mandate pre-FFCRA (Appendix Table 10). Eighth, we include weekend days in the sample (Appendix Table 11). Ninth, as a form of placebo test, we include only weekend days, i.e., days on which PSL should be less important. Results are smaller in magnitude relative to the main sample and are thus in line with our hypothesis (Appendix Table 12). Finally, we show that results are robust to clustering on the day[17] and using heteroscedasticity robust standard errors, see Appendix Tables 13 and 14 respectively.

6. Discussion

On January 30th, 2020 the World Health Organization (WHO) declared the coronavirus 2019 (COVID-19) outbreak a Public Health Emergency of International Concern (PHEIC) and on March 11th, 2020 the organization officially declared it a global pandemic (World Health

[16] We note that individuals do not need to take up the benefits within two weeks. However, this specification potentially allows us to model pent-up demand for PSL related to COVID-19 that was not available to many workers prior to this time period.

[17] We note that we have just 25 clusters in this specification.

Organization 2020a). The COVID-19 pandemic has caused large losses in lives, and severely affected labor markets. For example, in the U.S. there were 6,211,406 initial unemployment insurance claims in the week ending March 28th, 2020 which reflects a 2,763% increase over the number of claims in the week ending February 29th, 2020 (216,982)[18] and the pandemic is predicted to result in a severe global recession (International Monetary Fund 2020). In addition, the pandemic has reignited discussions of perceived inadequacies in U.S. social policy, including a lack of a national, universal PSL mandate (Cain Miller 2020).

We offer the first evidence on the impact of FFCRA on physical mobility (presence at home and at work), a proxy for social distancing. By providing many public and private sector workers up to two weeks of PSL to employees who are sick (whether confirmed as COVID-19 infected or not) and/or must care for children who cannot attend school or daycare, or tend to sick family members, FFCRA represents the first national PSL policy in the U.S. We combine high frequency data based on more than 20 million cellular devices' (individuals') GPS locations to track physical mobility measured at the county-level. Because FFCRA affects the nation as a whole and thus does not offer a clean comparison group, we use interrupted times series analyses to study this Act. The data show a compelling pattern of that FFCRA induced people to refrain from working and to stay home.

Following the federal Act, those individuals who gain access to PSL related to COVID-19 were more likely to stay home and less likely to work. In particular, we document a 17.7% decrease in full time work and 7.5% increase in staying home immediately following FFCRA adoption, with effects dissipating after eight to 22 days. Results from a modified difference-in-differences approach that exploits variation across counties in physical mobility prior to FFCRA

[18] Authors' calculations based on Department of Labor Unemployment Insurance Weekly Claims Data (https://oui.doleta.gov/unemploy/claims.asp; last accessed May 5th, 2020).

is also consistent with the conclusion, and numerous alternative specifications and samples add to the robustness of the results.

Given that 17% to 47% of employees are potentially eligible for FFCRA benefits, our effect sizes are arguably non-trivial. The correct denominator for calculating effects of treatment on the treated is unclear. While approximately a quarter of U.S. employees were not previously eligible for PSL, the extent of FFCRA PSL maybe more generous than earlier available to some. Furthermore given large losses of employment, the composition of PSL available among remaining workers may be different. The exemption for small employers provides further uncertainty regarding the number of workers for whom this new provision would apply. In sum, we show that mandated PSL reduces time spent at work and promotes staying home while sick or to meet family responsibilities. As data become available on how many employees have received benefits under this law, further discussion of effect sizes will be possible.

Our findings contribute to three economic literatures. First, our work adds to the literature that explores the impact of PSL mandates in the U.S. Our work complements previous work, which has focused on state and local mandates, by examining an Act that affected the nation. In addition, unlike existing PSL mandates, FFCRA is a temporary Act that is designed to offer immediate, but tailored, support to employees and their families, and society at large, during an unprecedented outbreak of a highly infectious disease. Second, we add to the recent surge in economic research on government responses to infectious disease. A theme in this literature is to study the impact of policies that encourage social distancing. In that spirit, we consider how providing employees with financial support impacts social distancing.

Our study has limitations. Our measure has many short comings in terms of reflecting the medically advised social distancing concept we would ideally study. However, to the extent our data accurately capture time at work and presence in the house, these are arguably the measures more likely affected by the FFCRA. Another important caveat is that we are not able isolate why individuals take leave: to recover from COVID-19 or to care for dependents. Future work from surveys that discern the reasons for staying away from work would enable further understanding. Given that FFCRA benefits mean larger changes in leave availability for different populations, additional difference-in-differences models based on percent of employees in a county that are eligible for additional leave would help add robustness to our results. While a potentially advantageous 'bite' variable is the share of eligible employees, there is no data we know of that would allow us to measure this variation. Our data are able to track mobility only up to three and a half weeks after the Act became effective. While we find substantial effects that begin immediately and dissipate by three weeks after the start of the policy, future work should explore longer data series, for example, to see whether there is an increase in use of these benefits among workers who return to their jobs after non-essential business closures are eased.

Despite limitations, we offer crucial timely first evidence on the impact of FFCRA on physical mobility, a proxy for social distancing. Since the aim of this temporary PSL law is to reduce externalities in workplace illness and to reduce caregiver burdens, understanding whether workers responded by decreased time in the workplace and increased time at home is vital first step to assessing the effects of the law.

Table 1. Summary statistics pre-FFCRA: SafeGraph Social Distancing Metrics

Variable	**Mean/proportion**
County-level outcomes:	
Share of devices working full-time (‘work full-time’)	0.175
Share of devices away from home less than one hour per day (‘at home’)	0.413
State-level social distancing policies	
Share with public school closure order	0.216
Share with stay-at-home order	0.044
Share with non-essential business closure	0.057
Share with restaurant dining-in prohibited	0.171
COVID-19 confirmed cases and deaths	
Share after first case in county	0.104
Share after first death in county	0.012
Share after first case in state	0.486
Share a first death in state	0.211
*N (county * day)*	163,430

Notes: Data source is SafeGraph Social Distancing Metrics files February 1st, 2020 until March 31st, 2020. Data are weighted by population. The unit of observation is a county in a day.

Table 2. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (baseline specifications): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
Panel A: ITSA		
FFCRA	-0.022***	0.042***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001*	0.011***
	(0.001)	(0.001)
Stay-at-home order	-0.001***	0.013***
	(0.000)	(0.001)
Non-essential business closure	0.000	-0.000
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001	-0.004***
	(0.000)	(0.001)
Panel B: 'Bite' design		
FFCRA*bite	-0.805***	0.629***
	(0.033)	(0.116)
State-level social distancing policies		
Public school closure	0.004*	0.009
	(0.002)	(0.006)
Stay-at-home order	-0.005*	0.008
	(0.002)	(0.006)
Non-essential business closure	-0.004	-0.010
	(0.002)	(0.008)
Restaurant dining-in prohibited	-0.001	0.033***
	(0.003)	(0.010)
Number of counties in the sample	2,770	2,770

Panel A notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

Panel B notes: Data source is SafeGraph Social Distancing Metrics files February 2nd, 2020 to April 24th, 2020 (the month of March is dropped); weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects, and fixed-effects for each day in the study period. Standard errors are clustered at the county-level and are reported in parentheses.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Table 3. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (allow for interaction between previous local PSL mandate with FFCRA): SafeGraph Social Distancing Metrics

Outcome	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.022***	0.043***
	(0.000)	(0.001)
Time	-0.001***	0.002***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.004***
	(0.000)	(0.000)
Interactions between FFCRA and pre-ACT local PSL mandate		
*PSL mandate	-0.004***	0.005***
	(0.001)	(0.001)
State-level social distancing policies		
Public school closure	-0.001*	0.011***
	(0.001)	(0.001)
Stay-at-home order	-0.001**	0.013***
	(0.000)	(0.001)
Non-essential business closure	0.000	0.001
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001	-0.004***
	(0.000)	(0.001)
Number of counties in the sample	3,114	3,114

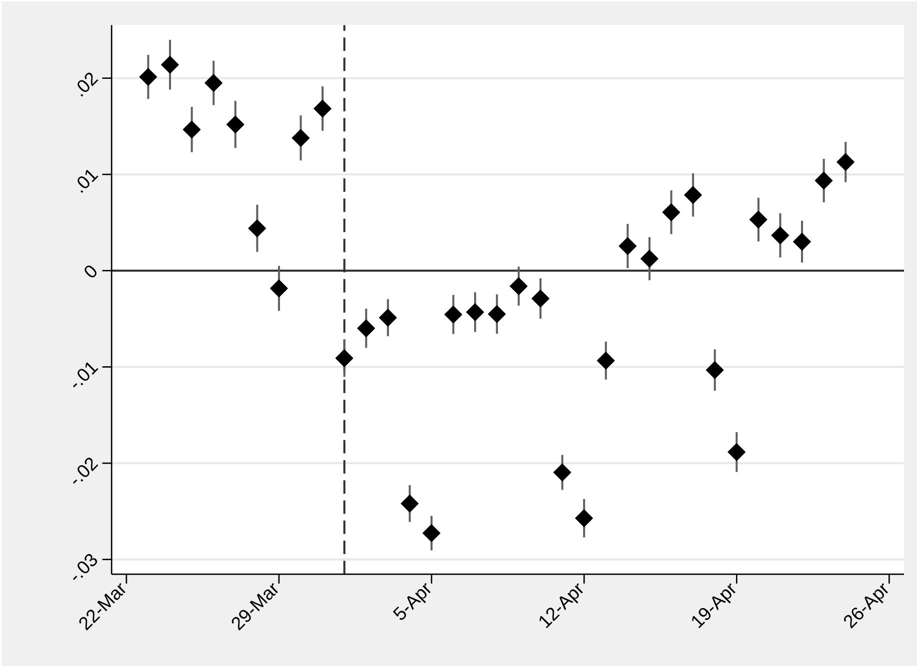
Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. The sample includes counties with a pre-FFCRA PSL mandate. See Appendix Table 1 for pre-FFCRA PSL mandate information. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.
***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Table 4. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (allow for interactions between race, ethnicity, and blue collar employment share and FFCRA): SafeGraph Social Distancing Metrics

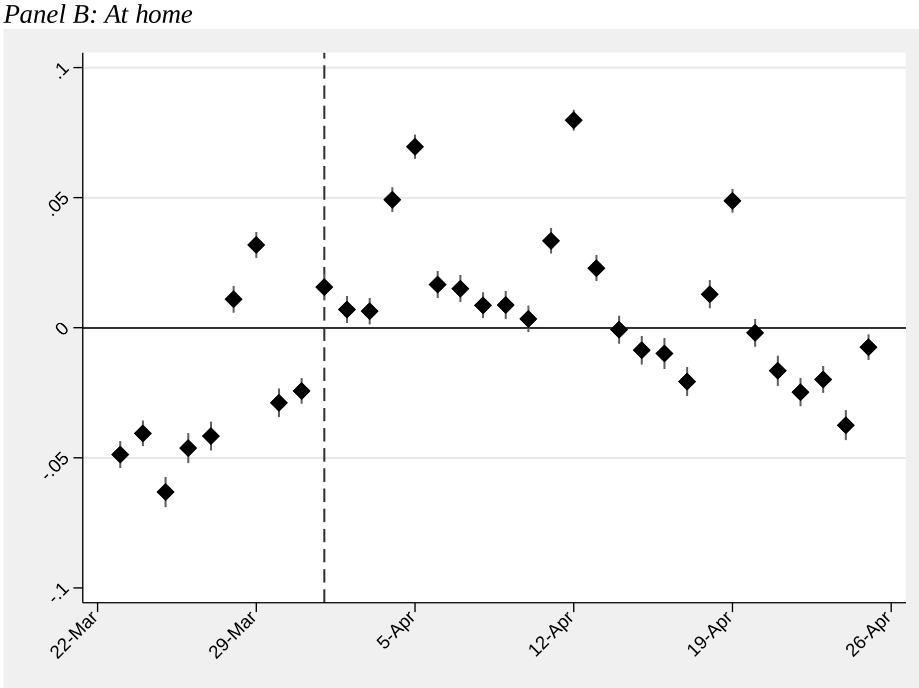
Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.021***	0.039***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
Interactions between FFCRA and local PSL mandate		
*African American	0.016**	-0.029
	(0.006)	(0.015)
*Other race	-0.005	0.008
	(0.003)	(0.007)
*Hispanic	0.001	0.015***
	(0.002)	(0.004)
*Blue collar	-0.013***	-0.005
	(0.004)	(0.008)
*College degree	-0.028***	0.017
	(0.006)	(0.012)
State-level social distancing policies		
Public school closure	-0.001	0.011***
	(0.001)	(0.001)
Stay-at-home order	-0.002***	0.014***
	(0.000)	(0.001)
Non-essential business closure	0.000	-0.001
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001	-0.004**
	(0.001)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.
***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Figure 1. Trends in physical mobility measures: SafeGraph Social Distancing Metrics
Panel A: Full-time work



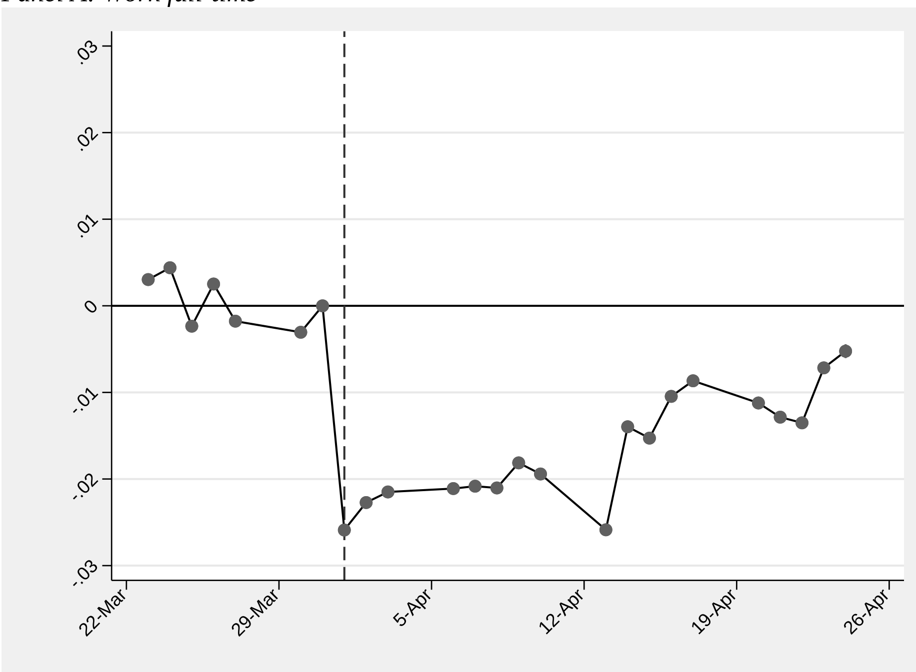
Panel B: At home



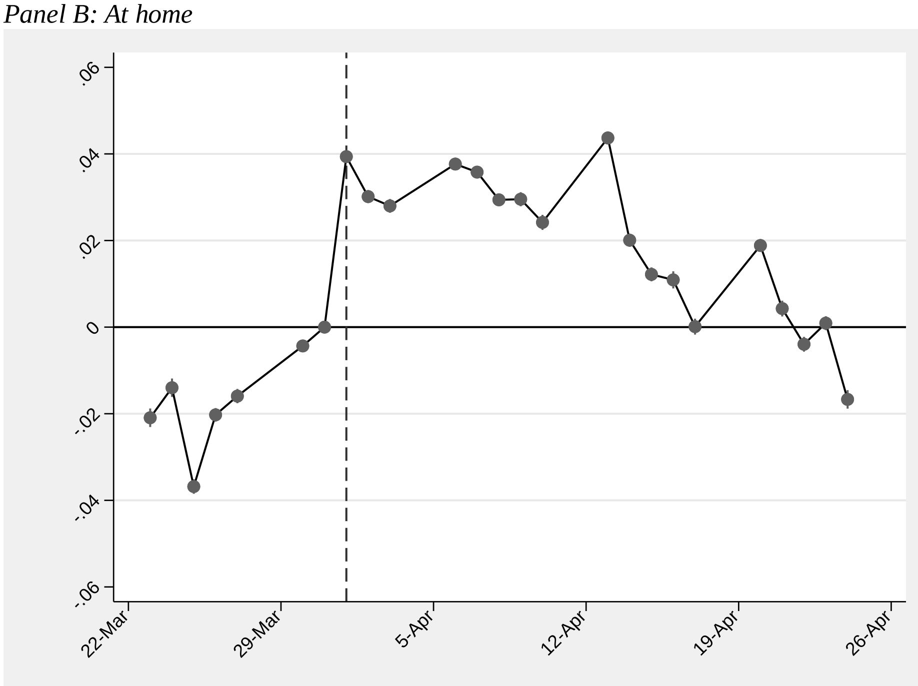
Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends omitted. Data are weighted by population. The unit of observation is a county in a day. Data are demeaned using the grand mean over the full study period. The vertical dashed line indicates April 1st, 2020.

Figure 2. Effect of FFCRA on physical mobility measures using an event-study design: SafeGraph Social Distancing Metrics

Panel A: Work full-time



Panel B: At home



Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends omitted. The omitted category is March 31st, 2020. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Coefficient estimates are reported with black circles. 95% confidence intervals account for within-county clustering and are reported with vertical lines. The vertical dashed line indicates April 1st, 2020.

Appendix Table 1. Access to paid sick leave in the U.S. among civilian employees: National Compensation Survey 2019

Category	Percent with access to paid sick leave
All employees	76
Employee occupation	
Management, professional, and related	91
Management, business, and financial	94
Professional and related	90
Teachers	87
Primary, secondary, and special education school teachers	96
Registered nurses	90
Service	61
Protective service	83
Sales and office	76
Sales and related	64
Office and administrative support	83
Natural resources, construction, and maintenance	68
Construction, extraction, farming, fishing, and forestry	59
Installation, maintenance, and repair	77
Production, transportation, and material moving	70
Production	68
Transportation and material moving	72
Employee job characteristics	
Full-time	86
Part time	43
Union	91
Nonunion	73
Employee wage group	
Lowest 25 percent	51
Lowest 10 percent	31
Second 25 percent	79
Third 25 percent	88
Highest 25 percent	92
Highest 10 percent	94
Employer industry	
Goods-producing industries	72
Service-providing industries	76
Education and health services	87
Educational services	90
Elementary and secondary schools	93
Junior colleges, colleges, and universities	89
Health care and social assistance	85
Hospitals	94
Public administration	92
Employer size (number of employees)	
1 to 99	66
1 to 49	64
50 to 99	71
100 or more	85
100 to 499	81
500 or more	91

Notes: Data source: https://www.bls.gov/ncs/ebs/benefits/2019/ownership/civilian/table31a.pdf (last accessed May 5th, 2020).

Appendix Table 2. Localities with pre-FFCRA PSL mandates

Type of locality	Specific locality name
States	Arizona California Connecticut Massachusetts Maryland Michigan New Jersey Oregon Rhode Island Vermont Washington
Cites and counties	Berkeley, California Emeryville, California Los Angeles, California Oakland, California San Diego, California San Francisco, California Santa Monica, California Washington, DC Chicago, Illinois Cook County, Illinois Montgomery County, Maryland Duluth, Michigan Minneapolis, Minnesota Saint Paul, Minnesota New York City, New York Westchester County, New York Philadelphia, Pennsylvania Pittsburgh, Pennsylvania Seattle, Washington Tacoma, Washington Austin, Texas Dallas, Texas San Antonio, Texas

Notes: Data source: A Better Balance (2020).

Appendix Table 3. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (use a quadratic in FFCRA and time): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.024***	0.024***
	(0.000)	(0.001)
Time	0.001***	0.009***
	(0.000)	(0.001)
Time*Time	0.000***	0.001***
	(0.000)	(0.000)
FFCRA*time	-0.000***	-0.009***
	(0.000)	(0.001)
FFCRA*time*Time	-0.000***	-0.001***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001	0.009***
	(0.001)	(0.001)
Stay-at-home order	-0.001**	0.011***
	(0.000)	(0.001)
Non-essential business closure	0.000	0.000
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001*	-0.004***
	(0.000)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 4. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (include a dummy for the post-FFCRA period): SafeGraph Social Distancing Metrics

Outcome:	Work full-time	At home
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.021***	0.038***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.004***
	(0.000)	(0.000)
FFCRA + 14 days	0.005***	-0.017***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001	0.010***
	(0.001)	(0.001)
Stay-at-home order	-0.001**	0.011***
	(0.000)	(0.001)
Non-essential business closure	0.000	-0.000
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001	-0.005***
	(0.000)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 5. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (unweighted): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA unweighted mean (March 25th to 31st)	0.137	0.508
FFCRA	-0.024***	0.046***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001	0.016***
	(0.001)	(0.002)
Stay-at-home order	-0.002***	0.011***
	(0.000)	(0.001)
Non-essential business closure	-0.000	0.003***
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001**	-0.003***
	(0.001)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are unweighted. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses. ***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 6. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (exclude the state-level social distancing policies): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.022***	0.044***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files February 2nd, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.
***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 7. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (control for information events as proxied by first confirmed case and death in the county and state): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.022***	0.041***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001	0.012***
	(0.001)	(0.001)
Stay-at-home order	-0.001***	0.013***
	(0.000)	(0.001)
Non-essential business closure	0.000	0.000
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001	-0.004***
Confirmed COVID-19 cases and deaths		
First confirmed case in the state	0.000	0.001
	(0.000)	(0.001)
First confirmed death in the state	-0.000	0.001
	(0.000)	(0.001)
First confirmed death in the state	-0.001	-0.004***
	(0.001)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files February 2nd, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.
***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 8. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (use a longer pre-treatment period): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (February 1st to March 31st)	0.162	0.458
FFCRA	-0.007***	0.015***
	(0.001)	(0.002)
Time	-0.003***	0.008***
	(0.000)	(0.000)
Time*time	-0.000***	0.000***
	(0.000)	(0.000)
FFCRA*time	0.004***	-0.008***
	(0.000)	(0.000)
FFCRA*time*time	0.000***	-0.000***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.015***	0.056***
	(0.002)	(0.004)
Stay-at-home order	0.002	0.005
	(0.001)	(0.004)
Non-essential business closure	-0.005***	-0.002
	(0.001)	(0.004)
Restaurant dining-in prohibited	-0.001	0.021***
	(0.002)	(0.004)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files February 1st, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 9. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (use alternative outcomes): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time alternative proxy**	**At home alternative proxy**
Pre-FFCRA mean (March 25th to 31st)	0.140	0.621
FFCRA	-0.038***	0.043***
	(0.000)	(0.001)
Time	-0.000***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.004***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	0.000	0.008***
	(0.001)	(0.001)
Stay-at-home order	-0.001*	0.010***
	(0.001)	(0.001)
Non-essential business closure	0.001*	-0.000
	(0.001)	(0.001)
Restaurant dining-in prohibited	0.004***	-0.004***
	(0.001)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Work full-time alternative proxy = away from home for ten or more hours. At home alternative proxy = away from home for up to two hours per day. Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.
***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 10. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (include counties with a pre-FFCRA PSL mandate): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)┼	0.124	0.563
FFCRA	-0.023***	0.045***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.004***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.000	0.009***
	(0.001)	(0.001)
Stay-at-home order	-0.001	0.012***
	(0.000)	(0.001)
Non-essential business closure	0.001*	0.000
	(0.001)	(0.001)
Restaurant dining-in prohibited	0.002**	-0.005***
	(0.000)	(0.001)
Number of counties in the sample	3,114	3,114

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

┼Sample means are based on the main sample of counties without a pre-FFCRA PSL.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 11. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (including weekends): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)┼	0.124	0.563
FFCRA	-0.021***	0.028***
	(0.000)	(0.001)
Time	-0.001***	0.006***
	(0.000)	(0.000)
FFCRA*time	0.002***	-0.008***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.002***	0.010***
	(0.001)	(0.001)
Stay-at-home order	-0.002***	0.013***
	(0.000)	(0.001)
Non-essential business closure	0.001	-0.000
	(0.001)	(0.001)
Restaurant dining-in prohibited	-0.000	0.001
	(0.000)	(0.001)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are included. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

┼Sample means are based on the main sample of counties that excludes weekends.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 12. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (weekend days only): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)┼	0.124	0.563
FFCRA	-0.009***	-0.027***
	(0.001)	(0.003)
Time	-0.006***	0.021***
	(0.000)	(0.001)
FFCRA*time	0.007***	-0.024***
	(0.000)	(0.001)
State-level social distancing policies		
Public school closure	0.000	-0.005**
	(0.001)	(0.002)
Stay-at-home order	-0.001	0.017***
	(0.001)	(0.001)
Non-essential business closure	0.002**	0.007***
	(0.001)	(0.001)
Restaurant dining-in prohibited	0.000	0.011***
	(0.001)	(0.002)
Number of counties in the sample	2,770	2,770

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are included. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the county-level and are reported in parentheses.

┼Sample means are based on the main sample of counties that excludes weekends.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Table 13. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (cluster standard errors around day): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.022***	0.042***
	(0.002)	(0.004)
Time	-0.001*	0.003**
	(0.000)	(0.001)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.001)
State-level social distancing policies		
Public school closure	-0.001	0.011**
	(0.002)	(0.003)
Stay-at-home order	-0.001*	0.013***
	(0.001)	(0.002)
Non-essential business closure	0.000	-0.000
	(0.001)	(0.003)
Restaurant dining-in prohibited	0.001	-0.004
	(0.001)	(0.002)
Number of counties in the sample	2,770	2,770
Number of days in the sample	25	25

Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Standard errors are clustered at the day-level and are reported in parentheses.

***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

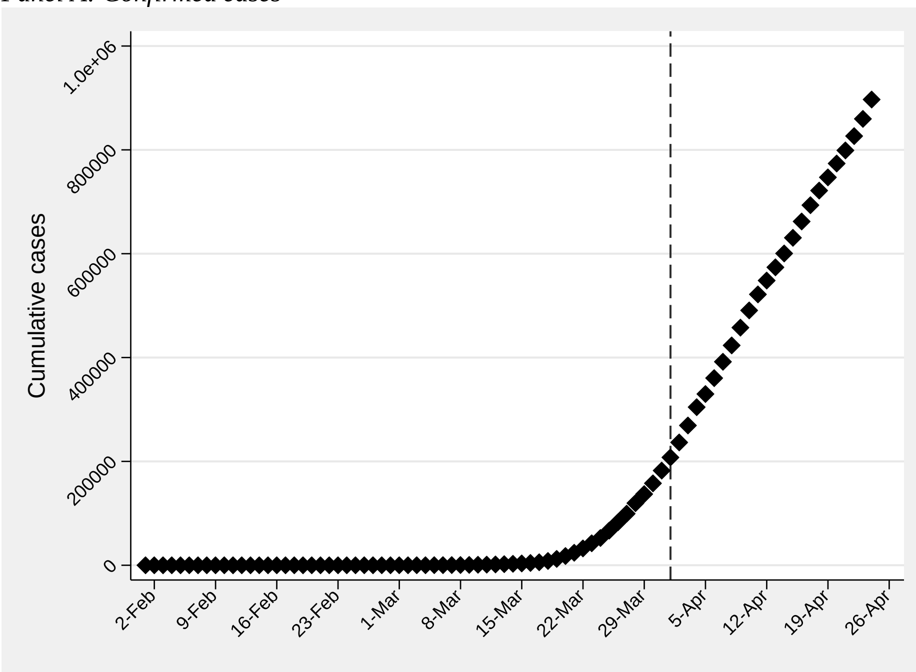
Appendix Table 14. Effect of FFCRA on physical mobility outcomes using an interrupted times series analysis model (heteroscedasticity robust standard errors): SafeGraph Social Distancing Metrics

Outcome:	**Work full-time**	**At home**
Pre-FFCRA mean (March 25th to 31st)	0.124	0.563
FFCRA	-0.022***	0.042***
	(0.000)	(0.001)
Time	-0.001***	0.003***
	(0.000)	(0.000)
FFCRA*time	0.001***	-0.005***
	(0.000)	(0.000)
State-level social distancing policies		
Public school closure	-0.001**	0.011***
	(0.000)	(0.001)
Stay-at-home order	-0.001***	0.013***
	(0.000)	(0.001)
Non-essential business closure	0.000	-0.000
	(0.000)	(0.001)
Restaurant dining-in prohibited	0.001*	-0.004***
	(0.000)	(0.001)
Number of counties in the sample	2,770	2,770
Number of days in the sample	25	25

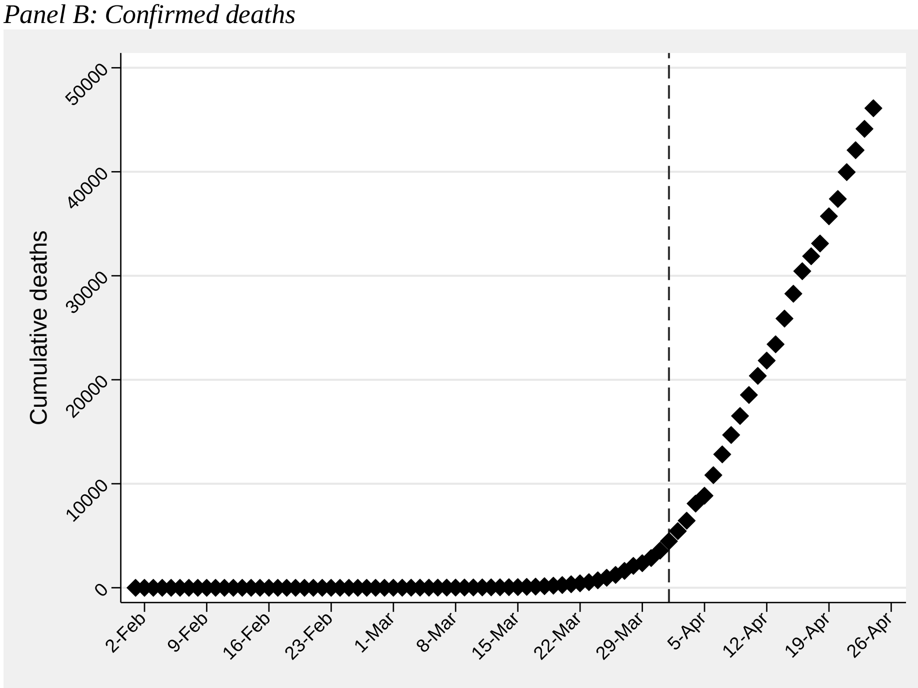
Notes: Data source is SafeGraph Social Distancing Metrics files March 25th, 2020 to April 24th, 2020; weekends are omitted. Data are weighted by population. The unit of observation is a county in a day. All models are estimated with LS and control for county fixed-effects. Heteroskedasticity robust standard errors are reported in parentheses. ***;**;* = statistically different from zero at the 0.1%, 1%, 5% level.

Appendix Figure 1. Trend in confirmed COVID-19 cases and deaths: Johns Hopkins University Coronavirus Resource Center

Panel A: Confirmed cases



Panel B: Confirmed deaths



Notes: Data source is Johns Hopkins University Coronavirus Resource Center confirmed COVID-19 cases and deaths March 25th, 2020 to April 24th, 2020; weekends omitted. The unit of observation is a county in a day. The vertical dashed line indicates April 1st, 2020.

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