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COVID-19 Emergency Sick Leave Has Helped Flatten The Curve In The United States

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ABSTRACT This analysis examines whether the coronavirus disease 2019 (COVID-19) emergency sick leave provision of the bipartisan Families First Coronavirus Response Act (FFCRA) reduced the spread of the virus. Using a difference-in-differences strategy, we compared changes in newly reported COVID-19 cases in states where workers gained the right to take paid sick leave (treatment group) versus in states where workers already had access to paid sick leave (control group) before the FFCRA. We adjusted for differences in testing, day-of-the-week reporting, structural state differences, general virus dynamics, and policies such as stay-at-home orders. Compared with the control group and relative to the pre-FFCRA period, states that gained access to paid sick leave through the FFCRA saw around 400 fewer confirmed cases per state per day. This estimate translates into roughly one prevented case per day per 1,300 workers who had newly gained the option to take up to two weeks of paid sick leave.

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The US is one of very few Organization for Economic Cooperation and Development (OECD) countries that does not guarantee universal access to paid sick leave for all workers.[1–4] Twenty-seven percent of all US employees and 17 percent of all US full-time employees cannot take paid sick leave. In the food and accommodation industries, more than half of all employees cannot take paid sick leave.[5,6]

Amid the outbreak of coronavirus disease 2019 (COVID-19), the question of whether a lack of paid sick leave contributes to the spread of disease has gained new relevance. Focusing on the pre-pandemic era, research has shown that employees who lack paid sick leave are more likely to go to work sick, have financial hardships, skip preventive health care, and spread contagious diseases.[7–14] Economic models suggest that "contagious presenteeism" behavior—working while sick with a contagious disease—decreases when employees gain access to paid sick leave, as they are more likely to stay home when ill.[15] Using variations in city- and state-level sick pay mandates across localities and over time, research has shown that increasing sick leave coverage causally reduces the spread of influenza.[15,16]

After fifteen years of partisan disagreement over the federal Healthy Families Act,[17] which proposes a federal sick leave mandate, the COVID-19 crisis led to the passage of a separate bipartisan emergency sick leave bill. On March 14, 2020, the House of Representatives passed the Families First Coronavirus Response Act (FFCRA), voting 340–40 in favor of passage. On March 18, 2020, the Senate approved the bill 90–8, and President Donald Trump signed it. The bill contains a provision that allows employees to take two weeks of COVID-19-related emergency sick leave coverage at full pay (up to a cap). In addition to other provisions, such as extended unemployment benefits, the bill also contains up to twelve weeks of paid family leave at two-thirds of daily pay for parents to take care of their chil-

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dren as a result of closures of schools and child care facilities.[18,19]

Businesses with more than 500 employees are exempt, so it is estimated that roughly half of the workforce is covered by the FFCRA.[20] Given that 89 percent of private-sector workers in firms with more than 500 employees already had access to paid sick leave,[5] the paid sick leave provisions primarily benefit workers in smaller firms who did not have paid sick leave before implementation of the FFCRA.[21] Surveys show that more than a quarter of covered firms actively make use of the law as of the beginning of May 2020.[22]

Previous research has shown that other policy measures such as stay-at-home orders and social distancing measures reduce the spread of the disease.[23–27] Using mobility patterns from cell phone data, research also shows that Americans spent significantly more time outside their workplace after the full FFCRA enactment April 1, 2020.[28] However, to our knowledge, this article is the first to test whether the FFCRA, and specifically its emergency sick leave provisions, reduced the spread of COVID-19.

Study Data And Methods

DATA SOURCES We compiled our main data set from various sources. First, we included the number of new reported COVID-19 cases for all US states from the COVID Tracking Project at the daily level.[29] Our data series starts March 8, 2020, and ends May 11, 2020. Because of both the focus on short-term infection dynamics and the statistical uncertainties related to estimating the fatality rate, we did not examine COVID-19 deaths in our analysis.[30,31] Second, we considered the number of daily tests performed. Third, we included policy measures such as stay-at-home orders as compiled by the Kaiser Family Foundation.[32] Fourth, we weighted our statistical regressions using state-level population counts from the Census Bureau to obtain representative estimates.[33] Fifth, we included data on state- and city-level sick pay mandates to determine our treatment and control groups.[34] In total, as of February 2020 twelve states and the District of Columbia had implemented state-level sick pay mandates, whereas thirty-eight had not. Finally, for additional evidence, we used data from Google Trends searches on emergency sick leave.

METHODS Our empirical approach was a difference-in-differences model estimated by ordinary least squares. To address concerns about the comparability of treatment and control states and to select our analysis sample, we first ran propensity score matching to focus on similar states.[35,36] In a robustness check, we built synthetic control groups to ensure common time trends.

The propensity score matching preselection identified seventeen states that we excluded from the analysis (Alabama, Arkansas, Idaho, Kansas, Maine, Missouri, Mississippi, North Carolina, North Dakota, Nebraska, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Virginia, and Wyoming).[36] Exhibit A1 in the online appendix shows relatively balanced covariate means by treatment status for several variables after propensity score matching.[37] In our main approach, we also omitted states that included cities with sick pay mandates (Illinois, New York, Minnesota, and Pennsylvania), as our analysis was at the state level and could not identify the exact origin of the reported cases.[38] However, in robustness checks, we included these states and assigned them partially treated values according to the population living outside these cities.

Our statistical models compared new cases at the state level for states that already had sick pay mandates in place before the COVID-19 pandemic (control group) with new cases in states where employees gained access to paid sick leave because of the FFCRA (treatment group). Our ordinary least squares model estimated the number of new cases by state by day through a linear combination of several variables: whether or not a state was part of the treatment group, with the variable set to 0 before implementation of the policy and 1 for all days on or after FFCRA implementation (our main variable of interest is effectively an interaction term between treatment states and time when the treatment started: Treat × FFCRA); day-of-week reporting effects; stay-at-home orders; and the number of daily tests carried out in the state. General nationwide virus dynamics in the US were taken out by sixty-five date fixed effects in our most saturated specifications (in others, we solely controlled for ten week fixed effects). State fixed effects controlled for structural, time-invariant differences in virus activity across states. Standard errors were clustered at the state level, and the regression was weighted by state population.[39–41]

By comparing changes in the outcome variable for treated states with changes in the outcome variable for control states and taking the difference, we present a difference-in-differences model. To give the coefficient on our main variable of interest a causal interpretation, one must assume that the outcome for the treatment group would have developed the same as the outcome in the control group absent the policy.[42]

In robustness checks we altered the effective date when the law became effective (March 18 versus April 1). We also ran robustness checks

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using the method of synthetic control groups following the standard methodology[43] (more detail is available in the appendix).[37] After building synthetic control states, we reestimated our model using the difference between each state and its synthetic control group as the outcome.

LIMITATIONS Our study had several limitations. First, our results pertain to a short-term perspective because our data end in May, about a month and a half after the implementation of the FFCRA. Second, in terms of the methods, although our matching models aimed to compare similar states, and we also controlled for a rich set of possible confounders, it is still possible that our approach did not capture relevant unobservables that increased the number of new COVID-19 cases in the control states. Finally, another potential limitation is that we were unable to investigate the underlying mechanisms of why COVID-19 cases decreased. Channels could have included reduced coworker or customer infections because sick employees called in sick instead of working sick, as well as reduced spread of infections through children. Specifically, the effect may also have operated through enhanced paid family leave and sick children who stayed home with their parents instead of being sent to child care when their parents gained access to paid sick leave. However, as we elaborate in the Discussion section, we think it is unlikely that the effect operated through paid family leave.

Study Results

Exhibit 1 presents the summary statistics of our main sample. During the study period, March 8–May 11, states reported a mean 353 new confirmed cases per day, produced by 2,749 tests, on average, that were carried out daily per state. The average state population size is 6.2 million. Overall, forty-three states (and all states after our propensity score matching preselection) had stay-at-home orders implemented between March 19 and April 7, 2020. Exhibit 1 also shows that 57 percent of our (unweighted) observations came from treatment states, as indicated by the variable "Treat." In total, our post–propensity score matching sample included 1,945 observations.

EXHIBIT 1

Summary statistics of the main sample per state and day, March 8–May 11, 2020

State-day-level variables	Mean	Standard deviation	Minimum	Maximum
New COVID-19 cases	353	601	0	4,305
Tests	2,749	6,320	0	165,227
Population	6,207,895	7,612,396	623,345	39,900,000
Share of population older than age 65	0.1655	0.0229	0.1105	0.206
Population per square mile	530	1,735	1	9,773
Gross domestic product per capita ($)	68,001	29,144	44,950	213,544
Unemployment rate, January 2020	0.0368	0.0091	0.024	0.06
Share of population insured	0.9289	0.0279	0.86	0.97
International airport passengers per capita[a]	2.35	3.91	0.0	21.72
Influenza vaccination rate ages 18–64[b]	34.73	4.02	26.37	42.05
Influenza vaccination rate ages 65+[b]	60.62	4.62	51.27	69.37
Precipitation[c]	2.9432	1.1947	0.5508	5.2540
Treat	0.5681	0.4955	0	1
FFCRA	0.3584	0.4796	0	1
Policy	0.6756	0.4683	0	1

SOURCES COVID-19 Tracking Project, Kaiser Family Foundation, Federal Aviation Administration, Department of Transportation, Census Bureau, Bureau of Economic Analysis, Bureau of Labor Statistics, Centers for Disease Control and Prevention, National Oceanic and Atmospheric Administration, National Centers for Environmental Information, A Better Balance, and Department of Labor. Specific sources for the variables are in appendix exhibit A1 (see note 38 in text). **NOTES** Data are per state and day from March 8 to May 11, 2020, and not weighted (1,945 observations). From March 8 to March 12, data from twenty-nine states are included, and for the remaining days, data from thirty states are included (seventeen treatment and thirteen control). "Treat," "FFCRA", and "policy" are binary variables. "Treat" is set to 1 for states in which workers gained sick leave coverage through the Families First Coronavirus Response Act (FFCRA) (treatment group) and 0 otherwise. "FFCRA" is set to 1 starting April 1, 2020, when the law went into effect, and 0 otherwise. "Policy" is set to 1 in states and days during which a stay-at-home order was in place and 0 otherwise. [a]Sum of number of passengers at all international airports divided by the state population; excludes the District of Columbia. [b]Average rates between January and May of each year 2016–18. [c]Average state-level precipitation (inches) between January and May of each year 2011–18.

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Exhibit 2 presents our main results. Each column represents one regression model where we add sets of control variables stepwise from left to right, starting with the most parsimonious model at the left and progressing to the most "saturated" model that replaces week and day-of-week fixed effects with date fixed effects and controls for stay-at-home orders and the number of tests performed on a given day. The more robust the main coefficient estimates are to these control variables, the less likely it is that they are correlated with unobservables driving the relationship to the outcome variable.

In exhibit 2, all models show statistically significant decreases in the number of reported new COVID-19 cases for states whose workers gained access to paid sick leave as a result of FFCRA (the "Treat × FFCRA" interaction term variable). Although the effect sizes varied slightly, the estimates were not statistically different across the six models, and the point estimates ranged between −376 and −495. Our preferred specification in model 6 suggests that there were 417 fewer reported cases per state per day in states where workers gained the option to take COVID-19-related sick leave through the FFCRA, relative to infection activity in March and relative to changes in infection activity in control states. The FFCRA emergency sick leave provision also may have been more generous than some of the sick leave available to workers in our control states. This would imply that our results are lower-bound estimates.

Interestingly, adding controls for stay-at-home orders barely changed our estimates of interest. Although controlling for state testing capacity at the time is important (a significant positive predictor of positive tests), differences in testing did not affect our main results.

In the appendix we replicated the findings using March 18 as the effective date (exhibit A3) and included partially treated states (exhibit A4) as well as all states (exhibit A5) in a standard difference-in-differences model.[37] Our results were robust to these checks.

There are no official numbers on when exactly employers communicated to their employees that they could take the emergency paid sick leave or when employees first called in sick as a result of the FFCRA because the act did not specify when employees could start taking emergency sick leave.[44] However, it appears likely that some infectious employees called in sick instead of working sick immediately after the FFCRA became law. Exhibit 3 presents the results of a Google Trends search showing that searches about the new sick leave option spiked between March 14 and March 18. We interpret Google Trends searches as an indicator of subsequent use shortly thereafter. In addition, Wei-Jie Guan and coauthors report that the virus has an incubation period interquartile range of two to seven days,[45] which fits our observed data pattern in appendix exhibit A6 very well.[37] Appendix exhibit A6 shows that infection curves in the treatment and control groups were basically identical in the pre-FFCRA period and then diverged with a widening gap between March 18 and April 1 before the full effect finally manifested around April 4, 2020. For these reasons, we ran our models with March 18 and April 1 as alternative treatment dates. The appendix also shows a robustness check using synthetic control groups (appendix exhibits A8 and A9).[37]

Exhibit 4 plots the difference—the treatment effect—between the two curves in appendix exhibit A6[37] in an event study–type model. We observe almost no trend and a straight flat line in the days before the FFCRA's enactment. From March 26, the net difference in reported cases between the two groups starts to decrease, first slightly and then substantially, to where the dif-

EXHIBIT 2

Estimated relationship between the Families First Coronavirus Response Act (FFCRA) and COVID-19 cases, 2020

Control variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treat × FFCRA	−436.325**	−428.076**	−375.583*	−494.868**	−482.134**	−416.956**
Policy		−66.469	−42.173		−107.515	−72.960
Tests			9.682***			10.208***
Constant	764.948***	809.859***	716.089***	782.169***	854.993***	746.867***

SOURCES COVID-19 Tracking Project, Kaiser Family Foundation, Census Bureau. **NOTES** All models included 1,945 observations. All models included state fixed effects. Models 1–3 included week and day-of-week fixed effects. Models 4–6 included date fixed effects. Robust standard errors are clustered at the state level but omitted here for readability (appendix exhibit A2 contains the full table including standard errors; see note 38 in text). "Treat," "FFCRA", and "policy" are binary variables, as described in the notes to exhibit 1. "Treat × FFCRA" is an interaction term between those two variables. "Tests" measures the number of tests carried out on that day (in thousands). Data are per state and day and exclude Illinois, Minnesota, New York, and Pennsylvania, as these states were partially treated, as explained in the text. Appendix exhibit A4 includes these four states in a robustness check. $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

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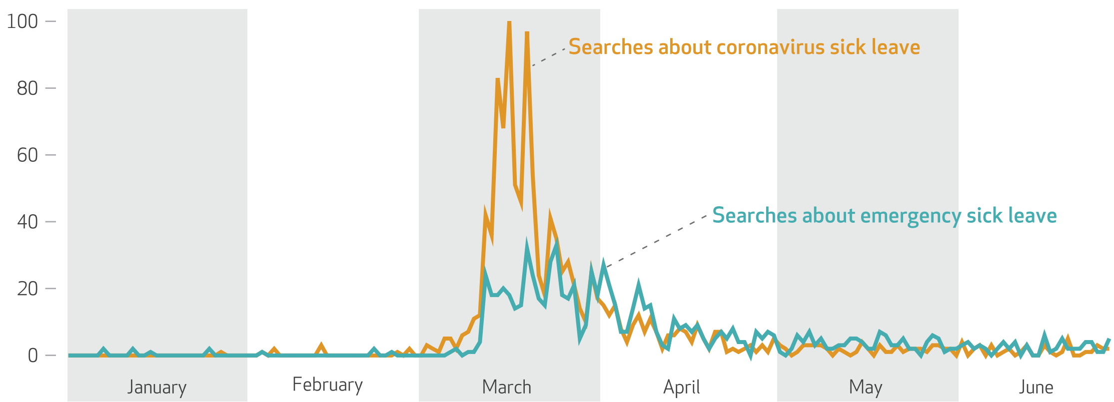
EXHIBIT 3

Nationwide Google searches on emergency sick leave and coronavirus sick leave in the US, January 1–June 26, 2020



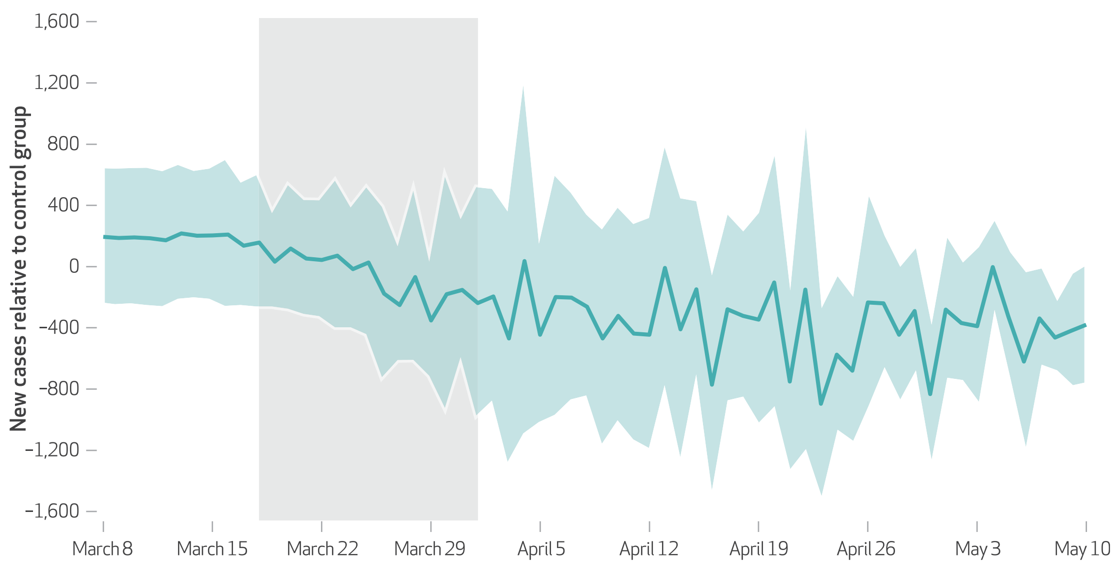
SOURCE Google Trends. **NOTES** The search trends show a spike in searches on emergency sick leave between March 14 and March 18. Google Trends normalizes search data to make comparisons between terms easier. Search results are normalized to the time and location of a query. Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics.

ferential remains about stable after April 1. Because of the statistical properties and noise, several daily point estimates are not statistically different from zero in a strict statistical sense. However, when estimated jointly as in the models in exhibit 2 and appendix exhibits A3–A5,[37] all but one of the twenty-four model estimates produced statistically significant postreform point estimates at conventional levels.

Another possibility to illustrate the effects is in

EXHIBIT 4

New COVID-19 cases in the US in the treatment group (states where workers gained the right to take paid sick leave) relative to the control group (states where paid sick leave was already provided), March 8–May 10, 2020



SOURCES COVID-19 Tracking Project, Kaiser Family Foundation, Census Bureau. **NOTES** The exhibit plots the coefficients of a regression of new cases on date fixed effects interacted with the binary variable "Treat," indicating the treatment group. The regression also controlled for testing capacities, state fixed effects, date fixed effects, and stay-at-home orders, as well as day-of-week reporting effects. The shading above and below the line denotes 95% confidence intervals. The left edge of the vertical shaded area indicates the date when the Families First Coronavirus Response Act (FFCRA) was signed into law (March 18). The right edge indicates the date when the law took effect (April 1). The figure excludes states with city-only paid sick leave (Illinois, Minnesota, New York, and Pennsylvania).

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appendix exhibit A7.[37] This is essentially appendix exhibit A6, but we took out common disease dynamics over time so that the exhibit shows group-specific deviations from the weekly mean of reported cases. The results clearly support our findings.

Appendix exhibits A8 and A9 present robustness checks using synthetic control groups.[37] Appendix exhibit A8 is similar to the previous figures. Moreover, although the effect sizes in appendix exhibit A9 decrease, the difference compared to exhibit 2 is not statistically significant, and the overall pattern of results is very similar.

As a final step, we discuss effect sizes. Relative to the mean number of new cases for the post-FFCRA period for the control group, which is 749, a decrease of 417 cases in our preferred specification in model 6 of exhibit 2 translates into a decrease of 56 percent. Although this effect appears large when viewed as a percentage, when put into context, it appears very reasonable. First, note that this is the effect of a policy that provided employees with the option to take paid sick leave in the midst of a highly infectious pandemic that had potentially exponential growth. Second, in a study during pre-pandemic times and focusing on rates of influenza-like illness, Stefan Pichler and Nicolas Ziebarth found that city-level sick pay mandates reduced these rates by about 40 percent in the first year.[14] In addition, Pichler and coauthors found that state-level sick pay mandates reduced official doctor-certified influenza-like-illness rates by about 30 percent in the short run.[15] Hence, these reductions are well in line with the existing causal effects literature on this topic.

Discussion

One of the bipartisan policy measures to combat the spread of COVID-19—the Families First Coronavirus Response Act, signed into law on March 18—included two weeks of emergency sick leave at full pay because of COVID-19. Our study used a difference-in-differences design to test whether this emergency sick leave provision reduced COVID-19 activity in the short run in the US. Our findings show that states where employees gained access to paid sick leave because of the FFCRA had a statistically significant decrease of approximately 400 fewer confirmed new cases per state per day relative to the pre-FFCRA period and to states that had already enacted sick pay mandates before enactment of the FFCRA.[29] Thus, granting access to paid sick leave has helped flatten the curve, in line with previous research and theoretical considerations. Prior research has shown that paid sick leave coverage induces contagious employees to take sick leave, thereby reducing influenza activity during normal times.[9,10,12,15,45] However, to date, it has been unclear whether this mechanism is also effective during the COVID-19 crisis.

As mentioned above, the FFCRA also contains up to twelve weeks of paid family leave at two-thirds of daily pay for parents to take care of their children because of the closures of schools and child care facilities. However, it is very unlikely that the paid family leave provisions are driving the effects, for several reasons. First, the two weeks of emergency sick leave studied here are paid at the full daily wage (up to a cap), whereas the twelve weeks of paid family leave are paid only at two-thirds the daily wage. Hence, even if eligibility criteria overlap, employees have a clear incentive to take their own sick leave first, at least in the short run, until the two weeks of emergency sick leave are depleted, which is the perspective taken here. Second, only a few states—California, New Jersey, New York, Rhode Island, and Washington—had paid family and medical leave laws in effect when the FFCRA was passed. This implies that gaining access to family leave is not systematically correlated with our definition of treatment and control groups. Third, emergency sick leave covers an individual's own sickness and would thus prevent contagious presenteeism. Paid family leave, in contrast, covers taking care of one's own children when their school or child care provider is closed for coronavirus-related reasons, which are mostly preventive and not because of children actually being infected. Although a child's sickness or quarantine on the advice of a health care provider are also qualifying reasons for FFCRA family leave eligibility, infection rates for children have been very low.[47] Finally, note that our empirical approach corrected for all laws and provisions through common (time) effects among all states.

Our statistical models compared new cases in states in which workers gained the option to take paid sick leave (under the FFCRA) with states where workers already had this option. All of our estimates are thus relative estimates after correcting for testing capacities, day-of-week reporting differences, general COVID-19 dynamics throughout the US, persistent state-level differences in virus activity, and stay-at-home orders. The FFCRA provided new coverage for about a conservatively estimated fifth of the workforce.[46] Hence, in a treatment state with an average population of 5.2 million, the FFCRA provided about half a million employees with a new option to take paid sick leave during the COVID-19 pandemic. Our findings show that it prevented about 400 confirmed cases per state per day, or about 1 case per 1,300 workers.

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Although our findings suggest that the emergency sick leave provision was a highly effective policy tool to flatten the curve in the short run, it only contains up to two weeks of paid leave and is set to expire at the end of 2020. If employees take their emergency sick leave as a precautionary measure or because they are quarantined for the standard time of two weeks, they obviously are unable to take paid sick leave again, which may force them to work sick and potentially spread the virus in the future. This is a particular risk during times of economic hardship, when employees are afraid of losing their jobs.

Infection rates in the US and Europe—two regions of comparable populations, labor markets, and decentralized COVID-19 policies—initially followed very similar curves. However, although new case numbers in Europe sharply declined after mid-April, they stayed elevated in the US and have gained new heights since mid-June. Whether and how the limited ability of US employees to take paid sick leave compared with already generous and additionally enacted COVID-19 provisions in Europe has played a role should be explored in future research. Recommendations by the OECD suggest that paid sick leave would continue to provide protection if countries' temporary expansions of paid sick leave were kept in place and access further expanded.[4] ■

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37 To access the appendix, click on the Details tab of the article online.

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