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Tanya Byker
Elena Patel
Kristin Smith

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1156 15th St NW Suite 700
Washington DC 20005
202-545-6002

Families First Coronavirus Response Act: Effect on Paid Leave Taking During the Early Pandemic

Tanya Byker* Elena Patel† Kristin Smith‡

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Abstract

We study the effect of access to Emergency Paid Sick and Family Leave on leave-taking behavior during the early months of the pandemic. We compare monthly paid absence from January – June, 2020, compared to these same months in 2018 and 2019 for eligible and ineligible employees based on firm size. Our evidence suggests that emergency paid leave increased leave taking by 68% and was primarily used for medical rather than child care needs. This result is driven by those workers at small firms who were not eligible for telework, consistent with constraints in access to emergency paid leave.

Keywords : paid leave, pandemic policy, social safety net
JEL Classification: J08, J38, H12

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*Middlebury College; tbyker@middlebury.edu
†David Eccles School of Business, University of Utah; elena.patel@eccles.utah.edu
‡Dartmouth College; kristin.e.smith@dartmouth.edu

1 Introduction

In the face of surging coronavirus cases and statewide lock downs, the federal government enacted the first federal mandate for paid sick and family leave on April 1, 2020 as part of the Families First Coronavirus Response Act (FFCRA). Although temporary and not universal, this bill was historic for a nation that remains the only OECD country lacking a paid leave mandate. To date, empirical evidence on the effectiveness of paid leave in the U.S. — whether sick, medical, or family leave — is based on state-specific policy variation. The FFCRA provides an opportunity to study the effect of a nationwide policy on leave-taking behavior during the onset of the COVID-19 pandemic.

We study the take-up of emergency paid sick and family leave during the initial months of the pandemic using monthly reported absences in the Current Population Survey (CPS). We use a differences-in-differences-in-differences (DDD) empirical framework to compare monthly paid absence in (1) January–March, 2020 (pre-pandemic) to April–June, 2020 (pandemic) relative to (2) these same months in 2018 and 2019, for (3) individuals eligible and ineligible for emergency paid leave. This design leverages eligibility exemptions in the Act based on firm size and job type. We find that workers without access to emergency paid leave exhausted all available paid leave at the onset of the pandemic, leaving them without access to paid leave later in the year. By comparison, access to emergency paid leave allowed employees to both accommodate the leave-taking needs of the early pandemic and subsequent leave-taking needs later in the year.

Our findings should be interpreted within the context of the onset of the pandemic, during which US workers were ill-equipped to accommodate a sudden and exogenous shock to leave-taking needs. While the majority of workers at private firms typically have access to some paid sick days, this leave is less than one week in duration, on average (Bureau of Labor Statistics, 2020). Furthermore, access to paid medical leave to care for own or a family member's serious illness is less widely available (Byker and Patel, 2021). Based on a nationally representative survey, Jelliffe et al. (2021) find that unmet leave-taking needs tripled during the early pandemic compared to pre-pandemic levels. The FFCRA expanded access to paid leave for employees who were unable to work due to own or family member illness or due to disruptions in childcare during the public health emergency. Our evidence suggests that the FFCRA was effective in allowing workers to accommodate employment disruptions during this time of heightened need.

We begin by estimating the change in paid absence from work that coincides with the pandemic, regardless of access to emergency paid leave. Based on a difference-in-difference model that compares monthly paid absence in 2020 to 2018 and 2019, we find that the pandemic increased paid absence by 79% in April 2020. However, by May 2020, paid absence had returned to pre-pandemic levels and had fallen fell below pre-pandemic levels by 51% by June, 2020. This reversal from April to June suggests that workers were constrained in their ability to take paid leave as the pandemic wore on — the elevation in paid leave usage in April, at the onset of the pandemic, came at the expense of leave needed later in the year.

Next, we study the effect of the FFCRA on paid absence for eligible employees. This analysis exploits restrictions in eligibility based on firm size using the DDD framework outlined above. Our results show that the FFCRA increased available paid leave to eligible employees such that they were able to accommodate both early and late leave taking needs. In contrast, ineligible employees appeared to have fully exhausted available paid leave early in the pandemic. We further restrict our analysis to those workers who were not likely to be eligible for telework, exploiting the fact that only employees who could not work from home work eligible for emergency paid leave. We confirm that our result is driven by the set of workers who were not likely to be eligible for telework, consistent with constraints in access to emergency paid leave.

Motivated by growing evidence of variation in leave-taking needs during the pandemic, we study heterogeneity in the effect of the FFCRA based on gender and parental status. For example, Heggeness (2020); Collins et al. (2021*b*,*a*) show that school shutdowns increased the need for leave-taking, especially for women. We examine the effect of the FFCRA—which included partially paid leave for the care of children due to childcare issues—by gender and based on the presence of young children in the home. However, we find the effect of the FFCRA is both economically and statistically similar for men and women and for adults with and without young children. This suggests that leave taken under the FFCRA was primarily used for medical rather than childcare needs, consistent with evidence based on administrative tax data (Goodman, 2021).

Our work contributes to a growing empirical literature studying the effect of expanded access to paid leave in the U.S. labor market. Much of the work in this area has been focused on the effect of access to paid *parental* leave to care for newborn children based on mandates in a handful of states; this literature finds substantial take-up of benefits among women with small-to-negative effects on labor force participation (Rossin-Slater, Ruhm and Waldfogel, 2013; Bailey et al., 2019). A more nascent literature studies the recent expansion of mandated *sick* leave at the state level; this literature finds an improvement in health outcomes, but inconclusive evidence on take-up and labor market outcomes (Ahn and Yelowitz, 2015; Pichler and Ziebarth, 2017; Stearns and White, 2018).

Finally, we contribute to new literature studying the take-up of FFCRA. Goodman (2021) documents the take-up of emergency leave at the employer level using administrative tax data; the evidence presented in his paper validates our empirical design, which compares employees at small and large firms. In addition, Jelliffe et al. (2021) provides survey evidence documenting the salience of emergency paid sick leave among workers, sick leave take-up, and unmet need for sick leave during the early onset of the pandemic. These papers note "low" levels of take-up and awareness, respectively.

We expand this literature in several important ways that allow us to refine estimated take-up and understand potential mechanisms. First, we study leave-taking using high-frequency data, providing necessary detail above and beyond the quarterly administrative tax data; these data are necessary to pinpoint the effect of the FFCRA on leave-taking early in the pandemic. These data are also rich in individual worker characteristics by examining employee responses, including based on firm, job, and employee characteristics. Our evidence based on employee-level data suggests that the FFCRA was more effective at expanding take-up of paid leave than as was found by Goodman (2021) based on employer-level tax records; these employer data may, again, have been too aggregated to have detected the short-term effect that we find using the rich CPS monthly data. Relatedly, the monthly CPS data allow us to implement a convincing empirical strategy that leverages variation in access based on the parameters of the policy and following sharp changes in take-up based on employer size seen in the administrative tax data (Goodman, 2021).

2 Background and Data

2.1 COVID-19 Pandemic: Impacts on Labor Market

The first confirmed case of SARS-COV2 in the United States was confirmed via testing on January 18, 2020. It would, however, take several more weeks for the U.S. case counts to rise to a level that triggered economic shutdowns. California was the first state to issue mandatory stay-at-home orders—a policy intended to stop the spread of the disease—on March 19, followed by New York on March 20, and Illinois and New Jersey on March 21. By March 25, all U.S. public schools were closed for in-person learning. By April 1, 35 states had implemented mandatory stay-at-home orders, fundamentally disrupting the US labor market. As a reflection of these sudden and jarring changes, the U.S. unemployment rate soared to 14.7% in April 2020 — the highest recorded unemployment rate in the post-World War II era.

2.2 Access to Paid Sick and Family Leave

Prior to the pandemic, there was no federal mandate to provide U.S. workers with wage replacement during absences from work. However, many workers had access to paid leave for certain approved health and family reasons, either voluntarily provided by their employer or mandated by the state or municipality where they worked. The policies and mandates for these paid leaves and the extent of access depends on leave-taking need.

Paid sick leave typically provides some wage replacement for absences due to short-term health needs and preventative care. At the beginning of 2020, paid sick leave was mandated in 10 states and 29 localities (Stearns and White, 2018; Maclean, Pichler and Ziebarth, 2020; Al-Sabah and Ouimet, 2021). According to the Bureau of Labor Statistics (BLS) National Compensation Survey (NCS), 75 percent of all private workers had access to at least some paid sick days in 2019. Typically, employees earn or accrue sick days in proportion to the number of hours they have worked. The NCS estimates that workers with access to paid sick leave and one to five years of tenure with a firm had, on average, seven paid sick days (and fifteen paid vacation days) per year in 2019 (Bureau of Labor Statistics, 2020).

Paid family and medical leave (PFML) relates to longer-term leave to care for own serious illness (medical leave), to care for a family member with a serious illness (family leave), or to bond with a new child (parental leave). At the beginning of 2020, 5 states had implemented PFML mandates (Byker and Patel, 2021). Unlike sick leave, PFMLs typically require a medical authorization, approval, and waiting period. The duration of leave in these states ranges from 8 to 52 weeks, and wage replacement rates range from 60% to 90%.

2.3 Details of the FFCRA Legislation

The leave mandate under the FFCRA expanded access to paid leave in two ways. The first covered up to two weeks of paid leave for certain qualified COVID-19 related reasons, including being sick or quarantining, and caring for a family member sick with COVID. This type of leave-taking was paid at a rate of 100% of an employee's normal wages - up to $511 per day. The second leave-taking need related to care for children whose school or childcare was closed for pandemic-related reasons. In this case, employers were required to pay 2/3 of normal wages — up to $200 per day — for up to 10 weeks of absence.

The FFCRA emergency paid leave programs were available to eligible employees — those who have been with their employer for at least 30 calendar days — of covered employers — those that employ fewer than 500 employees, beginning April 1, 2020.[1] Moreover, employers were not required to provide paid leave to employees that were capable of performing telework. The parameters of the policy are especially important given that (1) workers at small firms have less access to paid family leave, paid medical leave, and paid parental leave (Smith, 2019; Bureau of Labor Statistics, 2020) and (2) jobs that are not telework-compatible are typically lower paying jobs than those that can be preformed remotely (Dingel and Neiman, 2020). We will exploit these parameters for our identification strategy.

In an unprecedented move, the entire cost of wage replacement paid under emergency paid sick and family leave was funded by the federal government. Typically, state-mandated paid leave benefits are paid out of a trust fund that is funded through employer and/or employee payroll deductions that are paid by most employers and employees. In this case, employees were paid benefits directly by their employer who was, in turn, refunded 100% of the costs through a refundable payroll tax credit.

2.4 Data

Our analysis relies on data from 2018 to 2020 drawn from two components of the CPS: the basic monthly survey (BMS), which contains information about monthly leave taking, and the Annual Social and Economic Supplement (ASEC) which is fielded annually and contains detailed employer information. From the BMS, we observe whether a respondent was absent from work last week and whether this absence was paid or unpaid. In addition, we include demographic information such as gender, age, education, age, and number and age of children in the household. From the ASEC, we observe the size of a respondent's employer, measured by total number of employees, and an individual's occupation during

[1] Employers with fewer than 50 employees were exempt from this mandate if the requirement would "jeopardize the viability of the business as a going concern." In addition, employers of health care providers and emergency responders could exclude such employees from this program.

the last year.[2]

We impose two restrictions to these data. First, we limit our analysis to adults aged 21 to 59. Second, we limit our sample to those individuals who were (1) interviewed in the ASEC of the relevant year and (2) worked in the previous year. This latter restriction is required to ensure that we can measure firm size, a key determinant of access to paid leave under FFCRA. A practical consequence of this restriction is that we are limited to tracking monthly responses from January through June of each year.[3] However, these months allow us to study the effect of FFCRA on paid leave taking during the early months of the pandemic in 2020 compared to leave-taking patterns before the pandemic in 2018 and 2019.

Table 1 provides summary statistics for the individuals in our sample based on their responses in February of each survey year. Column (1) summarizes the individuals in our sample in 2018 and 2019, and column (2) summarizes the individuals in our sample in 2020. Generally, we see very little difference in the individuals in our sample during this control month (February) across all survey years. To begin, February labor force participation was 96%; this high rate of participation is driven by the restriction that we must make in order to observe firm size: as of March, individuals must have been employed in the previous year. In addition, 47% of our sample are women, 55% are married, 31% have young children (under 12 years old), 40% have a bachelors degree, 42% work in occupations that are telework compatible[4] , and respondents are 40 years old, on average.

The primary outcome in our analysis is paid absence from work during the reference

[2]Specifically, the ASEC asks a respondent to identify the number of persons who worked for their employer during the preceding calendar year across all establishments. Responses are categorized into the following groups: under 10, 10–24, 25–99, 100–499, 500–999, 1000+. The universe is persons age 15+ who worked during the preceding calendar year.

[3]This is because the CPS is structured as a short, interrupted panel − households are interviewed for four months and then they are out of the survey for eight months before being interviewed for another four months. Ensuring that every individual in our sample was observed in the ASEC, our sample includes individuals interviewed from two months before to three months after the ASEC interview in March.

[4]Dingel and Neiman (2020) design the original telework variable by reviewing the Work Context and the Generalized Work Activities questionnaires in the O*NET database. Occupations, in standard occupational classification (SOC), are defined as non- telework-compatible if respondents indicate that their work requires being outdoors, risking injury or illness, operating machines, performing physical activities, etc. All other occupations are identified as telework-compatible. Heggeness and Suri (2021) establish a binary telework variable by recoding the SOC format to fit CPS data.

week of the survey.[5] Columns (1) and (2) of Table 1 show that individuals in our sample had similar rates of paid leave-taking — roughly 1.5 % — in February across all survey years. At the same time, there is considerable variation in monthly paid leave taking behavior. Panel A of Figure 1 plots monthly paid leave taking in January–June of 2018, 2019, and 2020. Monthly paid leave taking was roughly 1% in January and February across all observed survey years; in other words, before the onset of the pandemic monthly paid leave taking patterns were similar. Pre-pandemic monthly leave-taking typically increases by 50% in March compared to January and February.

Although the onset of the pandemic and its effect of the US economy arrived in mid-to-late March, it does not appear that this induced notable changes in the share of individuals taking paid leave in March, 2020. While perhaps surprising, differences in paid leave taking in March 2020 will be muted by several factors. First, the onset of the pandemic and its effect on the US economy arrived in mid to late March. Second, the BMS is typically administered on a rolling basis throughout the month and references the last week's employment. Third, the administration of the CPS itself was affected by the onset of the pandemic. Fourth, and, most importantly, emergency paid leave was not available until April 1st.

In April 2020, paid absence increased sharply compared to typical leave-taking patterns. 2% of individuals were absent from work with pay in 2020, nearly twice as high as the typical April paid leave taking observed in the same month in 2019 and 2018. This increase and departure from the trend, however, was short lived. By May, the differences in paid leave taking disappears across survey years, and paid leave taking is even slightly lower in June 2020 compared to 2019 and 2018. We formally analyze the effect of the FFCRA in the context of these descriptive changes using a DDD methodology that we describe in the next section.

[5] Specifically, this variable identifies those individuals who were absent from work during the entire reference week with pay.

3 Methods

First, we formally compare monthly leave taking before and after the onset of the pandemic by employing a dynamic DD empirical specification

$$y_{imt} = \lambda_{2020} + \mu_m + \phi_m \cdot \mu_m \times \lambda_{2020} + X_{imt} + u_{imt} \qquad (1)$$

where y_{imt} is an indicator variable that identifies monthly paid work absences for individual i in month m in year t. We include monthly fixed effects, μ_m, omitting February as the reference category. λ_{2020} is an indicator for 2020, and X_{imt} includes control variables that explain monthly leave taking including state fixed-effects, state-level monthly COVID-19 case counts, and state-level total PPP loans,[6]and individual age and education. In this regression, ϕ_m identifies the DD coefficient; in other words, relative differences in monthly leave taking in each month from January through June 2020 compared to these same months in 2019 and 2018. All estimates are based on robust standard errors.

While ϕ_m coefficients identify the causal effect of the pandemic on monthly leave taking in 2020 compared to 2019 and 2018, these estimates also reflect all environmental differences between the two time periods. The onset of the COVID-19 pandemic fundamentally altered the US economic and health landscape. In response, everyone — individuals, local, state, and federal policy makers, employers — altered behavior. For this reason, ϕ_m cannot identify the effect of emergency paid family leave separately from these other confounding factors.

In order to identify the specific effect of emergency paid leave on leave taking behavior, we exploit parameters of the policy by comparing employees that did and did not have emergency paid leave access. Specifically, emergency paid leave was mandated for employees at firms with fewer than 500 employees (small firms) were mandated to have access to emergency paid

[6]Simultaneous to the passage of the FFCRA, the federal government created the Paycheck Protection Program (PPP) as part the Coronavirus Aid, Relief, and Economic Security (CARES) Act. The PPP provided forgivable, short-term, low-interest loans to qualified small businesses that could be used to pay payroll expenses or certain non-payroll operating costs. Take-up of PPP loans reduces the ability of employers to claim the emergency paid leave credit under the provisions of both Acts. Therefore, we control for the aggregate sum of PPP loans under \$250,000 issued in a given state.

family leave (treated employees), whereas employees at firms with more than 500 employees (large firms) were ineligible for emergency paid family leave (control employees). Because we cannot identify which employees specifically took emergency paid leave, comparisons based on differential access estimate an intent-to-treat (ITT) effect. Our use of the discontinuity in take-up of leave credits based on firm size is consistent with a documented increase in take-up at the 500 employee threshold based on administrative tax data (Goodman, 2021).

We formally make this comparison based on the following DDD empirical specification

$$
\begin{aligned}
y_{imt} \quad = \quad & \lambda_{2020} + Small_i + \mu_m + \mu_m \times \lambda_t + \lambda_{2020} \times Small_i + \mu_m \times Small_i + \\
& \gamma \cdot \mu_m \times \lambda_{2020} \times Small_i + X_{imt} + u_{imt} \qquad (2)
\end{aligned}
$$

where $Small_i$ is an indicator variable identifying those respondents who worked in the last year for an employer with fewer than 500 employees. In this specification γ identifies the DDD coefficient; in other words, differences in monthly leave taking in each month from January through June 2020 compared to these same months in 2019 and 2018 for employees at small firms compared to large firms. As before, differences in February leave taking serve as the reference group, and standard errors are clustered at the state level.

In order for these estimates to be interpreted as causally due to the FFCRA, access to emergency paid leave must be the only reason for differences in paid leave take-up during the pandemic across employees at large and small firms. While we cannot formally test this assumption, we provide evidence that treated and control employees were similar across a range of demographic characteristics in February 2020 compared to February 2019 and 2018. Columns (3)–(6) of Table 1 report mean characteristics control and treated employees, respectively. Most notably, employees at large firms are more likely to be female and are more highly educated. While employees at large firms are 30% more likely to be absent with pay, these February differences are similar in 2020, 2019, and 2018.

We formally test for balance in pre-pandemic employee characteristics based on a DD specification that differences among individuals at large and small firms in February, 2020 to differences in 2019 and 2018. Column (7) of Table 1 reports mean differences, and column (8) includes state fixed effects. We find that that treated employees are slightly less likely to have a bachelors degree (1.55 pp, or 3.4%) and are slightly less likely to have young children (1.6 pp, or 5%) in February of 2020 compared to 2019 and 2018, and these differences are statistically significant at the 5% level. In light of this, we include both characteristics among the set of control variables in our empirical analysis. Along all other dimensions, individual observable characteristics are balanced. Finally and most importantly, differences in the likelihood of paid absence are both statistically and economically insignificant.

4 Analysis

4.1 Effect of the Pandemic on Monthly Leave Taking

Panel (a) of Figure 1 plots the share of individuals absent from work with pay in each month from January through June of 2018 (dashed grey line), of 2019 (solid grey line), and of 2020 (solid black line). These data reveal several important things. First, monthly paid absence from work exhibits cyclicality: workers are almost three times as likely to be absent from work with pay in June compared with January. Second, this cyclicality was stable across years before the arrival of the pandemic: there are neither statistical nor meaningful differences in monthly paid absence in January–March, 2020 compared with these same months in 2019 and 2018. Third, monthly paid absence diverges sharply in April 2020, and the timing of this divergence exactly coincides with the onset of the pandemic.

Panel (b) of Figure 1 plots estimates, including 95% confidence intervals, of the difference in monthly paid absence in 2020 compared to 2019 and 2018 based on Equation 1. Differences are plotted as percent changes relative to pre-pandemic February monthly paid leave taking. All estimates include controls for age, education, the presence of young children in the home, and state fixed effects. In addition, we control for pandemic-specific effects; specifically, we control for state-by-month COVID case counts and PPP loan amounts. These estimates are also reported in column (1) of Table 2.

Causal interpretation of these estimates requires that individual paid leave taking would have evolved similarly during the pandemic months (April–June) if not for the onset of the pandemic. Panel (a) provides descriptive reassurance that there was very little secular variation in paid leave taking in January – March of 2018, 2019, and 2020. Panel (b) reports formal estimates of these relative differences, which are both statistically and economically insignificant.

We find that individuals in our sample were 79% (0.00895/0.0114, Col. 1 Table 2) more likely to be absent from work with pay in April 2020, and this is statistically significant at the 1% level. This change represents a sharp divergence from the pre-pandemic months and trends, but this increase was also short-lived. Paid leave taking returned to pre-pandemic levels in May 2020, when the effect of the pandemic on paid leave taking was both statistically and economically indistinguishable from zero. Finally, paid leave taking was 51% (0.00580/0.0114, , Col. 1 Table 2) below typical June paid-leave taking in 2020, and this estimate is statistically significant at the 5% level. We interpret this pattern as evidence that all workers exhausted their stock of paid leave early in the pandemic and were subsequently constrained in taking planned or needed absences later in the year, as the pandemic wore on.

4.2 Effect of Access to Emergency Paid Leave

Next, we exploit the variation in eligibility for emergency paid leave based on firm size in order to identify the effect of the FFCRA. Panels (c) and (d) of Figure 1 report monthly leave taking in 2020 compared to 2019 and 2018 separately for employees at large and small firms, respectively. As previously described, the DDD strategy compares pre- and post-pandemic leave taking for employees at small firms (the treated group) to employees at large firms (the control group).

Identification requires that differences in pre- and post-pandemic leave taking would have evolved similarly at small and large firms if not for access to emergency paid leave. We formally test for a violation of this identifying assumption by comparing differences in paid absence take-up using our DDD estimation strategy. Panel (e) reports these estimates, scaled by February pre-pandemic leave taking. We do not find evidence of differential paid leave taking in January or March, consistent with our underlying parallel trends assumption. Specifically, employees at small firms were 0.0257 percentage points less likely to take paid leave in January and were 0.133 percentage points less likely to take paid leave in March (Table 2, col. 2). Neither estimate is statistically or economically significant.

We find that employees at large and small firms were equally likely to increase paid absence in April, 2020; specifically, our DDD estimate shows that paid absences differed by just 1.8% (0.0000686/0.0131, col 2), an economically and statistically insignificant difference. Similarly, differences in paid absence across treated and control employees are small and statistically insignificant in May (18%, 0.00242/0.0131, col 2). By June, however, we estimate that treated employees are 68% more likely to take a paid absence compared to control employees (0.00892/0.0131).

The pattern of our DDD estimate suggest several things. First, although paid-leave taking behavior was similar among eligible and ineligible employees in April, ineligible employees must have taken employer-sponsored paid leave because they did not have access to FFCRA. Therefore, ineligible workers had likely depleted employer-sponsored paid leave in April and therefore could not take needed leaves as the pandemic wore on. Panel (c) reflects this behavior, where ineligible employees took less leave in June of 2020 than would be expected based on 2018 and 2019 trends. By comparison, eligible employees had access to an expanded pool of leave. Consistent with this, eligible employees are more likely to take paid leave during all the early months of the pandemic. These differences across eligible and ineligible employees lead to a positive estimated effect of access to the FFCRA in later months.

Next, we decompose our result among those workers in telework vs. non-telework compatible occupations. This comparison leverages further variation in eligibility and suggests a placebo test: paid absences for workers in telework compatible jobs should not be differential by employer size if the result is driven by the FFCRA. These results are shown in Figure 2 and reported in columns (3) and (4) of Table 2. We do not find evidence that telework-compatible employees took paid absence differentially across firm size, confirming our placebo hypothesis (panels (d) – (f)). In contrast, panels (a) – (c) show that our DDD estimate is entirely driven by those employees who work in non-telework compatible occupations. These employees are 144% more likely to take paid absence in June, 2020 (0.182/0.126, column (4) Table 2).

4.3 Heterogeneity by Gender and Kids Under 12

Next, focusing on workers in non-telework compatible occupations, we investigate heterogeneity in the impact of FFCRA across gender and presence of young children in the household. Figure 3 shows scaled results from estimating Equation 2 separately for men and women and for employees with and without children under 12 in the household. Columns (5) – (8) of Table 2 report point estimates.

Despite concerns that women had greater need for leave for paid absence during the early months of the pandemic, we find that women and men were equally likely to take a paid absence in June, 2020 due to the FFCRA. Specifically, men were 141% (0.0176/0.0125, col. 5) more likely to take paid absence, and women were 143% (0.0183/0.0128, col. 6) more likely to take paid absence. Our result for men is statistically significant at the 1% level. By comparison, our result for women is only marginally insignificant at the 5% level (t-statistic of 1.94); however, our sample size of female non-telework compatible employees is 28% smaller than men, reducing our ability to detect these effects with statistical precision.

Further, we estimate paid absences increased by 158% (0.0179/0.0113, col 7) and 117% (0.0186/0.159, col 8) for employees without and with children, respectively. Again, this implies that parents—who may have disproportionately needed leave to accommodate a remote learning and care-giving environment—were not more likely to benefit from the FFCRA. Our result for employees without young children is statistically significant at 1% level, whereas our result for employees with young children is not statistically significant at conventional levels (t-statistic of 1.82). As with gender subsamples, however, our empirical design is potentially underpowered to detect the effect of the FFCRA for parents of young children given their comparatively smaller sample size. While these subsample results may be surprising in light of documented care-giving struggles during the pandemic, they are consistent with evidence in the administrative tax data that the vast majority of emergency paid leave claims were for sick leave, rather than childcare issues (Goodman, 2021).

4.4 Additional Discussion: Labor Force Participation

Because a worker needs to be attached to an employer to be on paid absence from work, it is necessary to interpret our results in the context of potential shifts in employment and labor force participation within our sample. We directly analyze the effect of the pandemic on labor force participation based on Eqn 1 and report these results in column (1) of Table A.1. We find that the pandemic sharply reduced labor force participation which declined by 1.84 pp in April, 2020, and this decline is statistically significant at the 1% level. Labor force participation recovered steadily in May and June. By June, 2020 labor force participation was just 0.6 percentage points lower due to the pandemic, and this difference was not statistically significant.

It is possible that FFCRA had a direct effect on labor-force attachment and the sign of this expected impact is ambiguous. On the one hand, access to paid leave should increase attachment for the marginal worker who might otherwise have detached. On the other hand, longer leaves facilitated by the policy could increase separation if, for example, longer leaves impact preferences for working compared with home production. The remaining columns of Table A.1 report estimates of impact of FFCRA on LFP for those in our sample using Eqn 2. Column (2) reports results for the the full sample; the coefficient on March is very close to zero, while there is a negative and marginally significant coefficient in April. Moreover, we estimate negative but not statistically significant changes in participation in May and June. Furthermore, columns (3)-(8) show LFP estimates for our subsamples and show similarly small and statistically insignificant impacts of FFCRA by occupation type, gender and presence of young children. All together, this analysis suggests that selection out of labor force is not driving our results for paid absence.

5 Conclusion

Early empirical analyses of the effect of the emergency paid leave under the FFCRA suggest that the provision was less successful than originally envisioned. According to administrative payroll tax data, 45 percent of firms sized 100-300 claimed credits for emergency paid leave through the first quarter of 2021 Goodman (2021), and the Congressional Budget Office estimates that the total cost of the credit was just 5% of projected costs ($5.4 billion claimed compared to a projection of $108 billion) Congressional Budget Office (2021). In addition, a small, nationally representative survey (n=371) conducted at the end of 2020 estimates that 5.4 percent of workers (estimated 8 million) took paid leave under FFCRA Jelliffe et al. (2021). Our analysis expands on these aggregate estimates by studying *who* took up paid leave during the early months of the pandemic, allowing us to address outstanding questions about the reach and effectiveness of the policy. Leveraging the detailed monthly data in the CPS, we find that the act helped eligible workers ease constraints imposed by limited access to paid sick leave on the eve of the pandemic.

We find similar rates of paid absence in the first month the pandemic across eligible and ineligible workers. However, only workers eligible for FFCRA — those at small firms with non-telework compatible jobs — were able to additionally take paid absences later in the year as the pandemic wore on. In contrast, ineligible workers seem to have exhausted any accumulated sick days at the onset of the pandemic and had depressed levels of paid absence later in the year. Monthly data allow us to detect this temporal variation to understand the mechanisms behind the takeup rates seen in the aggregate data.

Further, our ability to investigate subgroups of workers by gender and parenthood status allows us to investigate which elements of the FFCRA were effective in meeting worker needs. Specifically, the FFCRA provided for two different types of paid leave: paid sick leave and paid family and childcare leave. We interpret homoegeneity in the response of men and women and in the response of parents and non-parents as evidence that the emergency paid *sick* leave was an effective policy tool to accommodate heightened leave taking needs during a sudden public health crisis. This is consistent with evidence in the administrative tax data, which was dominated by paid sick leave claims (Goodman, 2021). On the other hand, the homogeneity that we estimate is inconsistent with access to emergency paid leave meaningfully affecting take up of family care leave during a time of unprecedented disruptions to child care. Goodman hypothesizes this may be due to lower replacement rates and caps for leaves for childcare needs than for sick leave.

The ability to stay home afforded by paid sick leave has been shown to improve public health both before the pandemic Stearns and White (2018) and during the pandemic. Specifically, two papers study the impact of FFCRA on reducing physical mobility using GPS tracking of cellular devices Andersen et al. (2020) and improvements in health outcomes using COVID case counts Pichler, Wen and Ziebarth (2020). Our paper adds to this literature assessing the impact of the first federal mandate for paid leave in US history.

Table 1: Descriptive Statistics and Balance: February, 2018–2020

	Full Sample		Control Large Firms		Treated Small Firms		Large vs Small Balance	
	18–19	20	18–19	20	18–19	20		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor Force Participation	0.956	0.954	0.960	0.960	0.951	0.947	-0.00390	-0.00383
							(0.00329)	(0.00329)
Female	0.469	0.476	0.492	0.501	0.447	0.451	-0.00475	-0.00451
							(0.00785)	(0.00785)
Married	0.553	0.552	0.544	0.548	0.561	0.556	-0.00839	-0.00835
							(0.00787)	(0.00786)
Age	39.8	39.9	39.6	39.8	40.1	40.0	-0.301	-0.283
							(0.176)	(0.176)
Bachelors	0.399	0.417	0.457	0.482	0.346	0.354	-0.0170	-0.0154
							(0.00770)	(0.00765)
Young Kids	0.312	0.304	0.302	0.302	0.320	0.304	-0.0156	-0.0158
							(0.00726)	(0.00726)
Earnings	60,433	66,558	66,179	75,120	55,077	58,257	-5,761	-5,588
							(1,300)	(1,297)
Unemployment	0.0271	0.0254	0.0219	0.0223	0.0320	0.0283	-0.00412	-0.00419
							(0.00263)	(0.00263)
Telework Compatible	0.418	0.4385	0.453	0.4755	0.384	0.4011	-0.00544	-0.00447
							(0.00791)	(0.00789)
Paid Absence	0.0114	0.0118	0.0131	0.0130	0.00980	0.0106	0.000892	0.000963
							(0.00168)	(0.00168)
State Fixed Effects								✓
Observations	64,464	64,464	30,720	30,720	33,744	33,744	64,464	64,464

Notes: This table reports summary statistics for the individuals in our sample in February of 2018, 2019, and 2020. To be included in our sample, an individual must have been employed in the prior year as reported in the March ASEC. Columns 1 and 2 report summary statistics for our full sample, columns 3 and 4 report summary statistics for individuals working at employers with more than 500 employees in the previous year, and columns 5 and 6 report summary statistics for individuals working at employers with fewer than 500 employees in the previous year. Column 7 reports mean differences for employees at big and small firms in February, 2018–2019 compared to February, 2020. Column 8 reports these same differences based on a regression that includes state fixed effects. Robust standard errors are reported in columns 7 and 8.

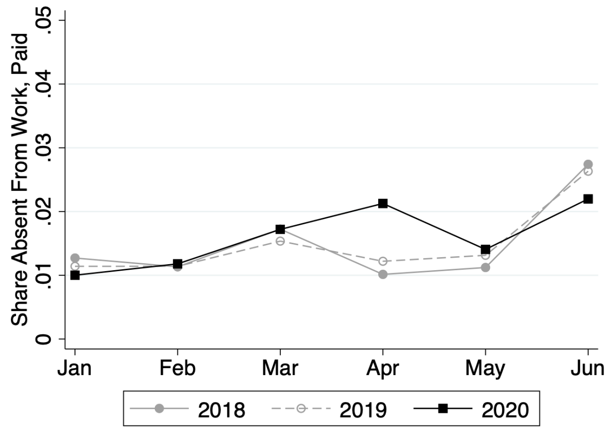
Table 2: DD and DDD Estimates: Changes in Paid Absence

	Baseline		Telework Eligibility		Gender		Children Under 12	
			Yes	No	Male	Female	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
January	-0.00242	-0.000257	-0.00556	0.00369	0.00437	0.00176	0.00234	0.00687
	(0.00130)	(0.00262)	(0.00402)	(0.00348)	(0.00441)	(0.00557)	(0.00391)	(0.00713)
March	0.000442	-0.00133	-0.00547	0.00179	-0.00149	0.00522	-0.00229	0.0113
	(0.00121)	(0.00242)	(0.00376)	(0.00319)	(0.00406)	(0.00517)	(0.00360)	(0.00650)
April	0.00895	6.86e-05	0.000113	-0.000452	-0.00205	0.00199	0.000451	-0.00296
	(0.00162)	(0.00276)	(0.00407)	(0.00381)	(0.00479)	(0.00625)	(0.00437)	(0.00757)
May	0.000939	0.00242	0.00352	0.00168	0.00409	-0.00219	0.00163	0.00139
	(0.00159)	(0.00290)	(0.00434)	(0.00398)	(0.00481)	(0.00668)	(0.00462)	(0.00774)
June	-0.00580	0.00892	-0.00222	0.0182	0.0176	0.0183	0.0179	0.0186
	(0.00250)	(0.00480)	(0.00851)	(0.00528)	(0.00602)	(0.00945)	(0.00616)	(0.0102)
Control Mean	0.0114	0.0131	0.0136	0.0126	0.0125	0.0128	0.0113	0.0159
Effect of Pandemic (DD)	✓							
Effect of FFCRA (DDD)		✓	✓	✓	✓	✓	✓	✓
Not Telework Compatible				✓	✓	✓	✓	✓
N	470,279	470,279	198,947	271,332	157,623	113,709	188,437	82,895

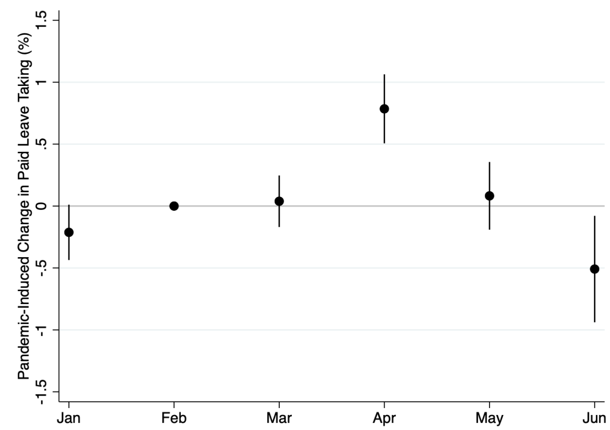
Notes: This table reports estimates of the change in likelihood of taking paid leave due to the pandemic based on equation 1 in column (1) and the effect of access to FFCRA emergency paid leave on the likelihood of paid leave-taking using 2 in columns (2) –(8). Columns (1) and (2) report baseline estimates based on all individuals in our sample, as described in Section 2 and 3. Columns (3) and (4) further restrict our analysis to those individuals who worked in telework ineligible jobs, further leveraging the eligibility criteria of the FFCRA. Columns (5) and (6) report the effect of access to FFCRA separately for men and women, respectively. Columns (7) and (8) report the effect of access to FFCRA separately for those without and with children under 12 in the household, respectively.

Figure 1: Monthly Paid Absence from Work

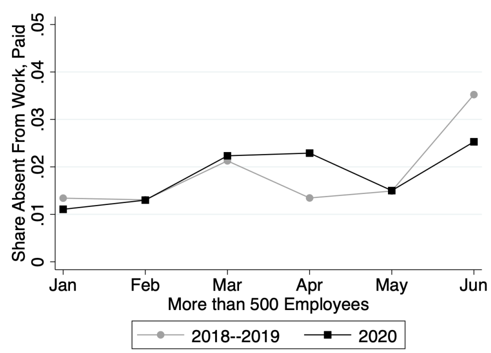
(a) 2018–2020



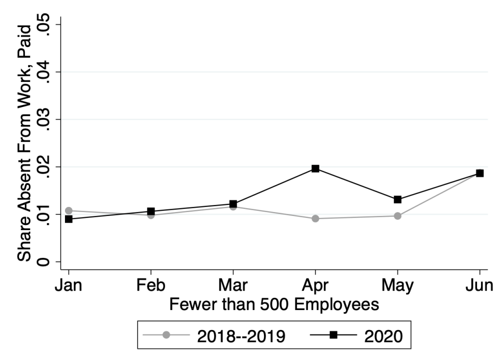
(b) DD: 2020 vs 2018, 2019



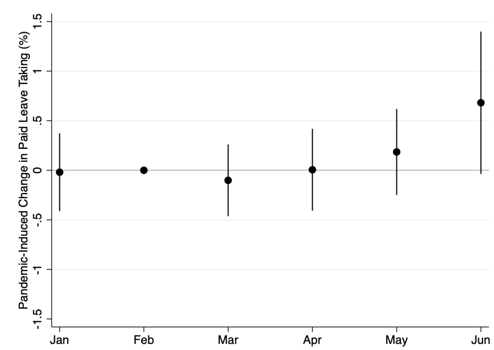
(c) Control Firm DD: 2020 vs 2018–2019



(d) Treated Firm DD: 2020 vs 2018–2019



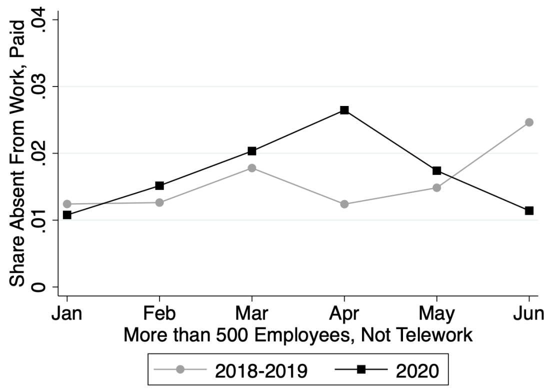
(e) DDD: Treated vs Control Firms



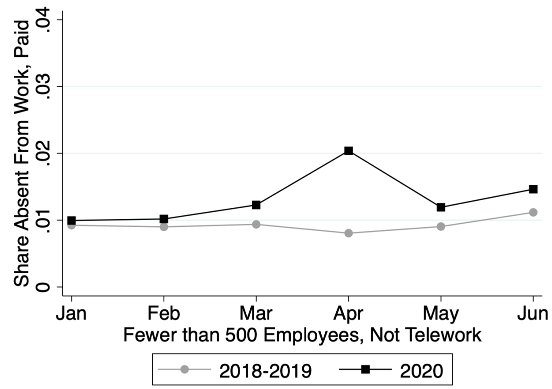
Notes: This figure reports monthly take up of paid leave for those individuals our analysis sample based. See Section 2 for a detailed data description. Panel (a) plots monthly mean take up of paid leave. Panel (b) plots DD estimates—scaled by pre-pandemic average take up—and 95% confidence intervals based Equation 1. Panel (c) plots mean monthly leave taking for individuals employed at large ($\geq$ 500 employees) and small ($<$ 500 employees) Panel (d) plots DDD estimates—scaled by pre-pandemic average take up—and 95% confidence intervals based Equation 2.

Figure 2: FFCRA-Related Changes in Monthly Paid Absence from Work: Telework Compatibility

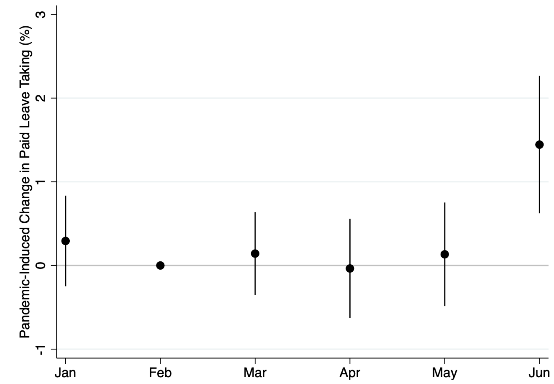
(a) Control Firms: Non-Telework-Compatible



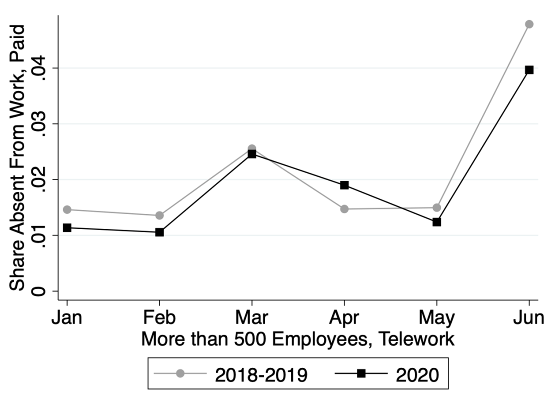
(b) Treated Firms: Non-Telework-Compatible



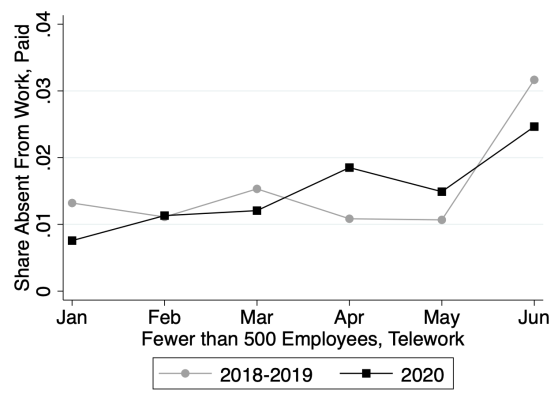
(c) DDD: Non-Telework-Compatible



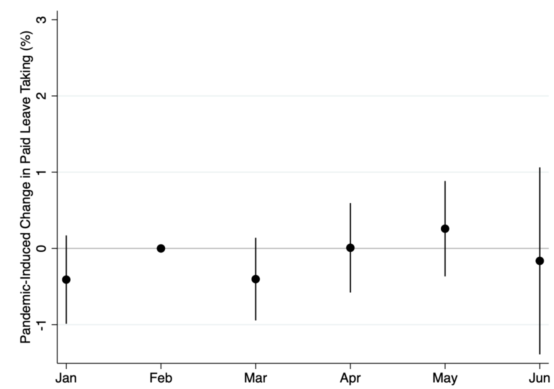
(d) Control Firms: Telework-Compatible



(e) Treated Firms: Telework-Compatible

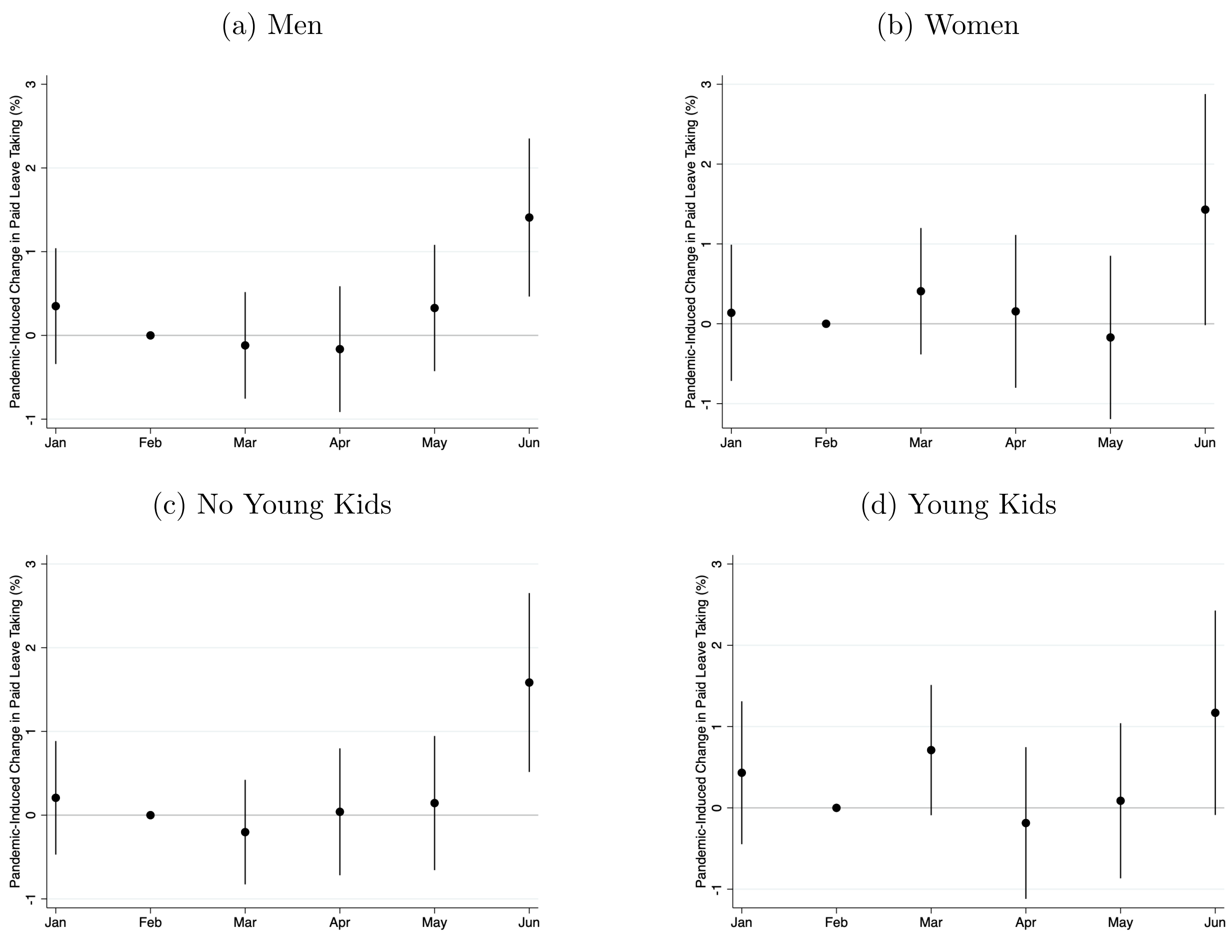


(f) DDD: Telework-Compatible



Notes: This figure reports monthly take up of paid leave for those individuals our analysis sample based based on the telework-compatibility of their job. See Section 2 for a detailed data description. Panels (a) and (b) plot monthly mean take up of paid leave for employees in non-telework compatible jobs at control firms (more than 500 employees) and treated firms (respectively), respectively. Panel (c) plots the corresponding DDD estimates—scaled by pre-pandemic average take up—and 95% confidence intervals based Equation 2. Panels (d) and (e) plot monthly mean take up of paid leave for employees in telework compatible jobs at control firms (more than 500 employees) and treated firms (respectively), respectively. Panel (f) plots the corresponding DDD estimates—scaled by pre-pandemic average take up—and 95% confidence intervals based Equation 2.

Figure 3: FFCRA-Related Changes in Monthly Paid Absence from Work: DDD: Non-Telework Compatible



Notes: This figure reports our estimate of the effect of access to FFCRA emergency paid leave based on equation 2. Panels (a) and (b) plot estimates for men and women, respectively. Panels (c) and (d) plot estimates for individuals with children under 12 in the household.

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A Appendix

Table A.1: DD and DDD Estimates: Changes in Labor Force Participation

	Baseline		Telework DDD		Gender DDD		Children DDD	
	DD	DDD	Yes	No	Male	Female	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DDD Point Estimates								
January	-0.000190	-0.00428	-0.00311	-0.00488	0.00435	-0.0177	-0.00577	-0.00272
	(0.00266)	(0.00530)	(0.00718)	(0.00762)	(0.00886)	(0.0135)	(0.00941)	(0.0128)
March	-0.00587	0.000924	0.00347	-0.000962	0.000421	-0.00385	0.00117	-0.00622
	(0.00217)	(0.00428)	(0.00587)	(0.00610)	(0.00718)	(0.0108)	(0.00744)	(0.0106)
April	-0.0184	-0.0122	-0.0130	-0.00965	-0.00158	-0.0246	-0.00991	-0.00942
	(0.00339)	(0.00553)	(0.00753)	(0.00792)	(0.00944)	(0.0138)	(0.00968)	(0.0137)
May	-0.0152	-2.76e-05	-0.00742	0.00879	0.0146	-0.00203	0.0121	0.00136
	(0.00342)	(0.00645)	(0.00857)	(0.00937)	(0.0112)	(0.0163)	(0.0114)	(0.0166)
June	-0.00613	-0.0109	-0.00478	-0.0123	-0.00272	-0.0284	-0.0166	-0.00123
	(0.00457)	(0.00883)	(0.0116)	(0.0129)	(0.0151)	(0.0231)	(0.0156)	(0.0233)
Control Mean	0.956	0.960	0.967	0.955	0.966	0.942	0.953	0.960
Not Telework Compatible				✓	✓	✓	✓	✓
N	470,279	470,279	198,947	271,332	157,623	113,709	188,437	82,895

Notes: This table reports estimates of the change in labor force participation due to the pandemic based on equation 1 in column (1) and the effect of access to FFCRA emergency paid leave on the likelihood of paid leave-taking using 2 in columns (2) –(8). Columns (1) and (2) report baseline estimates based on all individuals in our sample, as described in Section 2 and 3. Columns (3) and (4) further restrict our analysis to those individuals who worked in telework ineligible jobs, further leveraging the eligibility criteria of the FFCRA. Columns (5) and (6) report the effect of access to FFCRA separately for men and women, respectively. Columns (7) and (8) report the effect of access to FFCRA separately for those without and with children under 12 in the household, respectively.