Mandated Sick Pay:
Coverage, Utilization, and Welfare Effects

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March 16, 2020

Abstract

This paper evaluates the labor market effects of sick pay mandates in the United States. Using the National Compensation Survey and difference-in-differences models, we estimate their impact on coverage rates, sick leave use, labor costs, and non-mandated fringe benefits. Sick pay mandates increase coverage significantly by 13 percentage points from a baseline level of 66%. Newly covered employees take two additional sick days per year. We find little evidence that mandating sick pay crowds-out other non-mandated fringe benefits. We then develop a model of optimal sick pay provision along with a welfare analysis. Mandating sick pay likely increases welfare.

Keywords: sick pay mandates, sick leave, medical leave, employer mandates, fringe benefits, moral hazard, unintended consequences, labor costs, National Compensation Survey (NCS), welfare effects, optimal social insurance, Baily-Chetty

JEL classification: I12, I13, I18, J22, J28, J32

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[§]We thank Ronald Bachmann, Sonia Bhalotra, Nicholas Bloom, Chris Bollinger, David Bradford, Michael Burda, Colleen Carey, Eric Chyn, Michael Darden, Emilia deBono, Marcus Dillender, Gary Engelhardt, Itzik Fadlon, Jonas Feld, Laszko Goerke, Enda Hargaden, Sarah Hamersma, Sven Hartman, Matt Harris, Nathan Hendren, Martin Karlsson, Jing Li, Domenico Lisi, Norman Lorenz, Rick Mansfield, Fabrizio Mazzonna, Kathy Michelmore, Sean Murphy, Kathleen Mullen, Robert Nuscheler, Reto Odermatt, Alberto Palermo, Nico Pestel, Giovanni Pica, Joe Sabia, Kjell Salvanes, Seth Sanders, Brenda Samaniego de la Parra, Bruce Schackman, Georg Schaur, Bernhard Schmidpeter, Seth Seabury, Kathryn Shaw, Siggi Siegloch, Perry Singleton, Stefan Staubli, Holger Stichnoth, Alois Stutzer, Joanna Tyrowicz, Mark Unruh, Christian Vossler, Bruce Weinberg, Ansgar Wübker, Véra Zabrodina, and Maria Zhu for helpful comments and suggestions. In particular, we thank our discussants Priyanka Anand, Pascale Lengagne and Simona Gamba as well as Katherine Wen for excellent research assistance. Moreover, we thank participants at the American-European Health Economics Study Group meeting in Vienna, the Annual MaTax Conference at ZEW Mannheim, the Annual Conference of the American Society of Health Economists (ASHEcon) in Atlanta, the Annual Conference of the European Society for Population Economics (ESPE) in Antwerp, the Annual Meetings of the Southern Economic Association (SEA), the APPAM Fall Research Conference in Denver, the European Conference on Health Economics (EuHEA) in Maastricht, the 2018 and 2019 Annual Meetings of the Society of Labor Economists (SOLE), the International Health Economics Association (iHEA) in Basel, the 2019 IRDES-DAUPHINE Workshop on Applied Health Economics and Policy Evaluation, the 2018 IZA World Labor Conference, the 2019 NBER Workshop on Labor Demand and Older Workers in Cambridge, the 2019 SKILS seminar in Engelberg as well as in research seminars at the Center for Health Economics & Policy Studies (CHEPS) at San Diego State University, Cornell University, the Düsseldorf Institute for Competition Economics (DICE), HEC Montreal, IAAEU at the University of Trier, the Institute of Economics at the Università della Svizzera Italiana, ISER at the University of Essex, the Robert Wood Johnson Foundation (RWJF), Syracuse University, RWI Essen, the University of Augsburg, the University of Basel, the University of Ottawa, the University of Southern Florida, the University of Tennessee, and Weill Cornell Medicine for their helpful comments and suggestions. Last but not least we thank Maury Gittleman at the Bureau of Labor Statistics for helping us with numerous data questions. This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS. Generous funding from the Robert Wood Johnson Foundation's Policies for Action Program (#74921), the W.E. Upjohn Institute for Employment Research's Early Career Research Awards (ECRA) program #17-155-15 are gratefully acknowledged. Neither we nor our employers have relevant or material financial interests that relate to the research described in this paper. We take responsibility for all remaining errors in and shortcomings of the paper.

1 Introduction

Of all countries in the Organization for Economic Cooperation and Development (OECD), only three do not provide universal access to paid sick leave for employees: Canada, the United States, and Japan. Traditionally, in the U.S., employers voluntarily provide paid leave, which results in substantial inequality in coverage across jobs. For instance, 97% of private sector employees in the finance and insurance industry have access to paid sick leave while only 41% of employees in the accommodation and food services industry have access to this benefit in the U.S. (Susser and Ziebarth, 2016; Bureau of Labor Statistics, 2018b). Among low-income and part-time employees, coverage rates lie below 50% (Bureau of Labor Statistics, 2018b). Put differently, the majority of low-income employees cannot take a paid sick day to recuperate when they (or their children) become sick. Many employees are not even eligible to take an *unpaid* sick day as the only existing federal law, the The Family and Medical Leave Act of 1993 (FMLA), exempts part-time employees and employees in small employers. As of 2012, an estimated 44% (or 49 million) private sector employees were not covered by FMLA (Jorgensen and Appelbaum, 2014). In sum, the lack of federal regulation leads to a patchwork sick leave landscape with high degrees of inequality within the U.S. labor market.

A legislative initiative for a federal sick pay mandate—the Healthy Families Act—was spearheaded by Ted Kennedy. First introduced to the U.S. Congress in 2005, it was reintroduced in 2019 after several failed attempts to pass it (Senate Bill 840 - Healthy Families Act, 2019). In the meantime, numerous U.S. cities and states have passed similar sick pay mandates. San Francisco was the first locality to implement a sick pay mandate in 2007, increasing coverage rates above 90% among employees (Colla et al., 2014). Contrary to predictions of mandate opponents, San Francisco did not experience reduced labor demand or wage growth following adoption of this law (Boots et al., 2009; Drum Major Institute for Public Policy, 2010; Pichler and Ziebarth, 2020). Based on the San Francisco experience and widespread voter support—opinion pools suggest that 75% of Americans support sick pay mandates (National Paid Sick Days Study, 2010)—a wave of cities and states enacted sick leave legislation in the following years. As of writing, twelve states (including Arizona, California, Connecticut, Massachusetts, and Oregon), and twice as many cities and counties (including Chicago, New York City, Philadelphia, Portland, Seattle, and Washington D.C.) have passed sick pay mandates (see

A Better Balance, 2020 for an overview). More localities will likely adopt sick pay mandates in the coming years.

The canonical economic model of mandated job benefits predicts that employer mandates could be more efficient than direct government provision funded through taxation, if employees value the mandated benefit and accept lower wages from their employers in return (Summers, 1989). Gruber (1994), however, argues that anti-discrimination and minimum wage laws, as well as social norms, may prevent such wage reductions. In line with Gruber (1994), Pichler and Ziebarth (2020) find no evidence that U.S. sick pay mandates significantly and systematically reduced employment or wage growth. Because more widespread access to sick pay plausibly reduces presenteeism behavior ('working sick') as well as the spread of diseases within the workplace, sick leave mandates could even potentially *increase* work attendance and productivity (and thus wages) (Pichler and Ziebarth, 2017; Stearns and White, 2018). Besides productivity effects, laws and social norms, another reason for the absence of wage effects could be that the U.S. sick pay mandates are relatively mild government interventions, particularly relative to parental leave mandates.

Specifically, the mandates stipulate that employees have the right to earn one hour of paid sick leave per 30 to 40 hours worked for the employer. Such individualized sick leave accounts resemble medical savings accounts for health insurance, which intend to minimize moral hazard (Pauly et al., 1995; Keeler et al., 1996). This paper is the first to study the first order and welfare effects of mandating sick pay in the U.S. To do so, it builds on several important literatures: the existing research on inequalities in the labor market (cf. Autor et al., 2008; Song et al., 2019; Katz and Krueger, 2019) and parental leave (cf. Ruhm, 1998; Bartel et al., 2018; Campbell et al., 2019; Bailey et al., 2019) as well as the research on optimal social insurance (cf. Chetty and Finkelstein, 2013; Hendren, 2017) and employer mandates (Summers, 1989; Gruber, 1994).

Using official government data, this paper comprehensively evaluates the effects of state-level sick pay mandates in the U.S. We use variation produced by the staggered implementation of sick pay mandates across states and over time to evaluate their impact on coverage rates, sick leave utilization, and employer costs. These first order effects are of crucial relevance for academics and practitioners to assess the effectiveness and functioning of these mandates. Existing empirical evidence is scant and based on relatively noisy survey data (cf. Ahn and Yelowitz, 2016; Callison and Pesko, 2017). Further, this paper studies whether sick pay mandates have unintended consequences for employees. For instance, in response to the mandates, employers could reduce non-mandated fringe benefits such as paid vacation days or paid parental leave, all of which are potentially valuable to employees. To this end, we use restricted-access data from the National Compensation Survey (NCS) over the period 2009 to 2017 coupled with difference-in-differences (DD) models and event studies. These rich government data are specifically designed to measure full employee compensation and employer costs—indeed they are used to adjust federal employee compensation.

Our findings document that state-level mandates are effective in increasing coverage rates among U.S. employees. Within the first two years following mandate adoption, the probability that an employee has access to paid sick leave increases by 18 percentage points from a base coverage rate of 66%. The increase in coverage persists for at least four years without rising further. Over all post-mandate periods covered by this paper, we find a 13 percentage point higher coverage rate attributable to state mandates. As a result of the increased access to paid sick leave, employees take more sick days: we find an average increase in paid sick leave use by almost two hours per year. Scaling this two-hour increase by the 13 percentage points increase in coverage implies that newly covered employees take two additional sick days per year. Employer sick leave costs also increase, but effect sizes are modest. On average, the increase amounts to 2.7 cents per hour worked, which translates to an increase in 21 cents per hour worked for a marginal employer. Further, we find little evidence that sick pay mandates crowd-out non-mandated benefits such as paid vacation or holidays. Likewise, we find no evidence that employers curtail the provision of group policies such as health, dental, or disability insurance.

After empirically assessing mandate effects, we extend the standard Baily-Chetty framework of optimal social insurance benefits and develop an optimal sick pay model (see Baily, 1978; Chetty, 2006; Chetty and Finkelstein, 2013). In our model, when sick pay becomes more generous, the social planner weighs the marginally higher consumption utility of employees against the higher employer costs of providing more sick pay. As work productivity decreases in the sickness level, a profit maximizing employer will provide some level of sick pay voluntarily, even in the absence of a social planner. Otherwise, employees will work while sick and earn their regular salary, but their lower work productivity leaves them unprofitable for the employer. Sick pay incentivizes sick employees to call in sick and receive sick pay, αw, instead of the full salary w (with $\alpha w < w$). However, because employers solely maximize their profits while the social planner also considers employee utility, the optimal sick pay level set by the employer will be lower than the welfare maximizing level. Whether mandating sick pay increases welfare depends on the derived optimality condition. Accordingly, the marginal employee utility of more generous sick pay (1) must exceed marginal employer costs, and (2) this differential must equal the impact of more generous sick pay on employer production, specifically the changes in productivity and wage payments, weighted by the labor supply elasticity of more generous sick pay. When we feed the empirically identified parameter values into our derived optimality condition, we find that, for the most plausible and identified parameter values, sick pay mandates increase overall welfare.

The previous economic literature on U.S. sick leave is scarce. Gilleskie (1998, 2010) represent notable exceptions but these two important studies pre-date the current debate on sick leave mandates. Few studies empirically evaluate the recent U.S. sick pay mandates primarily due to a lack of data.[1] In an early but related study, Waldfogel (1999) shows that FMLA increased coverage rates and leave usage, in particular usage of parental leave. Note, however, that paid sick leave differs from parental leave in both aim and scope (Rossin-Slater et al., 2013; Lalive et al., 2014; Baum and Ruhm, 2016). Whereas sick leave coverage is an insurance against wage losses due to sickness, parental leave is mandated with the objective of balancing family and work responsibilities for employees, and addressing gender inequality in the workplace.

The paper proceeds as follows: Section 2 discusses the U.S. sick pay mandates in detail and Section 3 explains the data. The empirical approach and identifying assumptions are reported in Section 4. Section 5 discusses the empirical findings. Section 6 measures welfare effects by developing an optimal sick pay model. Section 7 concludes.

2 U.S. Sick Pay Mandates

Paid sick leave was an integral component of the first social insurance system in the world. The Sickness Insurance Law of 1883 implemented federally mandated employer-provided health insurance in Germany, which covered up to 13 weeks of paid sick leave along with health-

[1] The European literature on paid sick leave is much richer. Several studies find that employees adjust their intensive labor supply in response to changes in sick pay generosity (Johansson and Palme, 2005; Ziebarth and Karlsson, 2010, 2014; De Paola et al., 2014; Fevang et al., 2014). Other papers investigate interaction effects with other social insurance programs (Fevang et al., 2017), the role of probation periods (Ichino and Riphahn, 2005), culture (Ichino and Maggi, 2000), social norms (Bauernschuster et al., 2010), gender (Ichino and Moretti, 2009; Herrmann and Rockoff, 2012), income taxes (Dale-Olsen, 2013), union membership (Goerke and Pannenberg, 2015), and unemployment (Nordberg and Røed, 2009; Pichler, 2015). There is also research on the impact of paid sick leave on earnings (Sandy and Elliott, 2005; Markussen, 2012).

care. Insurance against wage losses due to health shocks was a crucial element of health insurance at that time, and valued by employees and unions alike. Given the limited availability of expensive healthcare treatments in the 19^{th} century, expenditures for paid sick leave initially accounted for more than half of all health insurance expenditures (Busse and Blümel, 2014). Subsequently, other European countries followed Germany's action and implemented paid sick leave coverage for employees. Today, every European country provides universal access to paid sick leave.

The U.S. is one of only three OECD countries without universal access to paid sick leave. As a result, in 2011, approximately half of U.S. employees did not have access to paid sick leave (Susser and Ziebarth, 2016). Since then, this share has decreased to below 30% (Bureau of Labor Statistics, 2018b). The only existing federal law is the Family and Medical Leave Act of 1993 (FMLA). This Act provides *unpaid* leave to employees in case of pregnancy, own sickness, or sickness of a family member to employees who work at least 1,250 hours annually for an employer with 50 or more employees (cf. Waldfogel, 1999). Given the exemptions to this law, Jorgensen and Appelbaum (2014) estimate that only 44% of private sector employees are eligible for FMLA. Susser and Ziebarth (2016) also document that many low-wage and service sector employees are either not covered by FMLA or not aware of their rights to the federally mandated benefit. Given this legislative landscape, although some exemptions exist especially for smaller employers, the sick pay mandates that we analyze in this paper allow many employees to take paid or unpaid sick leave for the first time.

Table A1 (Appendix) provides a detailed summary of most U.S. city- and state-level mandates passed at the time of writing. This paper evaluates all listed state-level mandates adopted between March 2009 and March 2017. While the details of the mandates differ from state to state, all existing mandates are employer mandates. Several mandates exclude small employers or allow for other exemptions. Under these mandates, employees 'earn' a paid sick leave credit; typically one hour per 30 to 40 hours worked with a maximum of seven days per year. If unused, the sick leave credit rolls over to the next calendar year. Because employees must accrue the paid sick leave credit, most mandates explicitly state a 90 day accrual period in addition to waiting periods for new employees. However, several mandates that exempt small employers compel such employers to provide *unpaid* sick days (Massachusetts Attorney General's Office, 2016).

San Francisco was the first locality to mandate paid sick leave in the U.S. The law became effective February 5^{th}, 2007. Washington D.C. enacted a mandate effective November 13^{th}, 2008, and expanded the scope of this mandate on Feb 22^{nd}, 2014 to include temporary and tipped employees. Other cities that have adopted sick pay mandates include Seattle (September 1^{st}, 2012), Portland (January 1^{st}, 2014), New York City (April 1^{st}, 2014), and Philadelphia (May 13^{th}, 2015).

Connecticut was the first U.S. state to mandate paid sick leave; the adoption date was January 1^{st}, 2012. The mandate only applies to service sector employees who work for large employers and, as a result, covers just 20% of the workforce. Over our study period, more states adopted sick pay mandates: California (July 1^{st}, 2015), Massachusetts (July 1^{st}, 2015), Oregon (January 1^{st}, 2016), and Vermont (January 1^{st}, 2017). Note that, in our empirical analysis, we treat Washington D.C. as a state. Additional states adopted mandates after the close of our study period: Arizona (July 1^{st}, 2017), Washington (January 1^{st}, 2018), Maryland (February 11^{th}, 2018), New Jersey (October 29^{th}, 2018), and Michigan (March 29^{th}, 2019).

Note that employers are generally required to post employee rights related to minimum wages, harassment, and discrimination protection as well as sick pay at the workplace. Figure A1 depicts two examples of such notices. Figure A1a shows an earned sick time notice for Massachusetts that employers could post to comply with that state's workplace poster requirements (Commonwealth of Massachusetts, 2019). Alternatively, employers can also post notices as in Figure A1b (here for Arizona) that include *all* employee right provisions that employers must comply with (Industrial Commission of Arizona, 2019).

Whenever state and city mandates coexist, legal complexities arise. When states pass mandates, existing city laws are typically preempted, as in the case of the 13 existing New Jersey city laws that existed prior to the state law (Title 34. Chapter 11D. (New) Sick Leave §§ 1-11).[2] However, preemption is not always the case, especially not when city laws are passed *after* the state law and are more comprehensive. Fortunately, the complexity of this city-state legal interplay is reduced in our setting because most state laws are very recent. Nevertheless, to facilitate the analysis, we disregard all sub-state mandates in our analyses. In particular, we drop the sub-state localities that have adopted sick leave mandates and evaluate only the state-

[2]See for the detailed bill https://www.njleg.state.nj.us/2018/Bills/AL18/10_.HTM, last accessed February 7^{th}, 2020.

level mandates.[3] To our knowledge, in California, Connecticut, Massachusetts, Oregon, and Vermont (states that offer policy variation in this paper), no sub-state laws have been passed after the state mandates became effective.

A final institutional point is worth mentioning. In several cases, sick pay mandates have been challenged through the court system, mostly by business groups seeking to have the laws overturned. For example, Airlines for America has sued the states of Massachusetts and Washington to seek an exemption from the law, arguing that the law would adversely affect their carrier prices, routes, and services (Bloomberg BNA - Workplace Law Report, 2018).[4] As another example of pending legal questions, the Massachusetts Supreme Judicial Court ruled that sick pay does not constitute wages, which implies that employers are not liable if they do not pay out unused sick days (Kaczmarek, 2018). In the empirical specifications, we do not differentiate by whether a lawsuit is pending anywhere at a given time for a specific jurisdiction.

3 National Compensation Survey (NCS)

We use the restricted access version of the NCS which is collected and maintained by the Bureau of Labor Statistics (BLS). These data include detailed information on geographic location of establishments, which allows us to accurately match state-level paid sick leave mandates to the data.[5]

The NCS is particularly well-suited to our research as it produces official government statistics on a wide range of compensation and labor cost items. The data are also used to officially adjust wages for federal employees. Further, the NCS includes information on access to paid sick leave, paid and unpaid sick leave utilization, and sick leave costs to employers. Moreover, the data allow us to explore potential spillovers from sick pay mandates to non-mandated benefits that employers could reduce to offset paid sick leave costs; for instance, paid vacation or parental leave.

[3] Our findings are broadly robust to including fully or partially treated sub-state localities. We note that these results are less precise and attribute it to sub-state mandates having less bite, as has been documented in other contexts. One reason could be pending lawsuits, see footnote 4. These results are available upon request. As noted, we treat Washington D.C. as a state and retain this locality in our empirical analysis.

[4] As an example at the city level, Pittsburgh approved a paid sick leave ordinance on August 3rd, 2015. However, shortly after, business groups sued and lower courts ruled against the law (due to unique language in the state's home rule charter). The city has appealed the decision to Pennsylvania's Supreme Court, where the case is currently pending (Moore, 2018). In case of Pittsburgh, enforcement of the law has been explicitly put on hold until a final decision is rendered.

[5] The restricted access version of the NCS that we use in this study is only accessible in a BLS data research center located in Washington D.C.

The NCS is nationally representative at the establishment-job level. In the NCS, random sampling is first carried out at the establishment level. The BLS defines establishments as 'a single economic unit that engages in one, or predominantly one, type of economic activity' (Bureau of Labor Statistics, 2020a). Second, within establishments, and depending on establishment size and number of different jobs within the establishment, the NCS collects information on compensation and benefits at the *establishment-job* level (Bureau of Labor Statistics, 2020a).[6]

The NCS is a quarterly survey, where human resource administrators of each establishment provide detailed information to the BLS surveyors on a range of offered benefits (including paid sick leave). Because the information is based on establishment-level administrative records, response error due to, for example, employees being unaware of their benefits is minimized. In our main analysis, we leave the microdata at the establishment-job level and restrict the sample to private sector establishments where the mandates apply. Moreover, we focus on the March responses of the first quarter interview because the BLS only provides information from this interview for many benefits (including access to paid sick leave). Basically, one can distinguish between stock and flow measures. The stock measures (such as access to paid sick leave) refer to the status quo at the time of the first quarter interview which takes place in March. The flow measures (such as sick leave utilization) generally refer to *the past 12 months*; that is, from April of the previous year to March of the survey year. Throughout our analysis, we use the survey weights provided by the BLS to provide nationally representative estimates. Henceforth, we refer to establishments as 'employers' in the manuscript.

[Insert Table 1 about here]

Table 1 reports the summary statistics. In our main sample, we have 399,586 observations at the employer-job level for the years 2009 to 2017. Using the Consumer Price Index, we convert all dollar values to 2017 U.S. dollars.

3.1 Main Variables

The main objective of our study is to comprehensively assess how sick pay mandates affect employer propensities to offer mandated and non-mandated benefits, employee utilization of

[6] Obviously, in our context, an ideal dataset would also be representative at the state-level, not just the federal level. To the best of our knowledge, no such dataset exists. To the extent that our identification assumptions hold, non-representativeness at the state level is no threat to the internal validity of our estimates.

paid and unpaid sick leave, and employer costs related to sick leave. Our first outcome variable measures employees' access to paid sick leave through her employer as of March in a given calendar year. *Sick leave offered* is coded one if a job provides paid sick leave and zero otherwise. Over all employers and years, the average coverage rate is 63% in our sample.

Our second outcome variable measures employees' use of paid sick leave. *Paid sick hours taken* indicates the average number of hours of paid sick leave taken by employees in this specific job in the previous 12 months (generally from April in the previous calendar year until the interview in March). The average is 15.8 hours, which corresponds to just under two days of paid sick leave.

Our third outcome variable measures employees' use of unpaid sick leave. *Unpaid sick hours taken* also generally refers to utilization over the past 12 months before the March interview. It may be a substitute to paid sick leave. The average is 0.65 per employee and year.

The final two main outcome variables measure employer sick leave costs. *Sick leave costs total* is the total hours of paid sick leave taken, multiplied by the hourly wage, inclusive of fringe benefits.[7] Again, following the flow measure concept of sick leave utilization, this measures refers to the past 12 months before the first quarter interview. Dividing the reported \$448.50 sick leave costs by the 15.8 paid sick hours taken yields a total hourly wage of \$28.35 for our sample. This number includes employer benefits; the gross wage paid to employees is \$21.69, see second panel of Table 1. *Sick leave costs per hour worked* divides *sick leave total costs* by the number of hours worked. The average is 25.1 cents per hour worked.

3.2 Additional Variables

We also assess whether mandated sick pay crowds-out non-mandated benefits. To meet this objective, we examine how sick pay mandates affect a range of fringe benefits and other forms of non-wage compensation. Table 1 lists such additional benefits. For example, on average jobs offer around 70 paid vacation hours and 44 national holiday hours per year.[8] Moreover, 69% of all jobs offer health insurance[9] and 57% offer life insurance coverage.

[7] The BLS NCS survey administrators generate this variable and use the employee's own wage in the calculation. The variable assumes that sick hours represent 100% lost labor and does not consider changes in employee on-the-job productivity because of sick pay, or compensatory behavior by employees after returning to work. Moreover, our data do not allow us to calculate the potential employer costs of finding a replacement for employees on sick leave.

[8] For vacation and national holiday hours, the BLS assumes that all offered hours are fully used.

[9] To be precise, here we use what the BLS labels 'medical insurance.' This variable does not necessarily cover prescription medications.

The remaining panels in Table 1 list control variables, or variables that we use to stratify the sample on to investigate effect heterogeneity. In particular, these are measures for full-time work, unionization, occupation, and industry. Approximately three quarters of the jobs in our sample are full-time jobs and just under ten% of jobs are unionized. The three most common occupations are 'office and administrative,' 'sales,' and 'food preparation and serving.' The three most common industries are 'healthcare and social assistance,' 'retail and trade,' and 'manufacturing.'

4 Empirical Approach

4.1 Difference-in-Differences

We use the staggered implementation of the sick pay mandates in different states at different points in time to estimate difference-in-differences (DD) models:

$$y_{e,j,t} = \gamma_{e,j} + \delta_t + \phi D_s \times T_t + \rho X_{e,j,t} + \mu_{e,j,t} \tag{1}$$

where $y_{e,j,t}$ is one of the outcome variables (e.g., *paid sick leave offered*) at employer e in job j and year t. $\gamma_{e,j}$ are employer-job fixed effects (which incorporate state fixed effects) and δ_t are year fixed effects from 2009 to 2017.

D_s is a treatment indicator, which is coded one for employers located within states that implemented a sick pay mandate between 2009 and 2017.[10] The interaction of D_s with the vector T_t yields the binary DD variable of interest. The interaction term is one for employers in states and time periods in which a paid sick leave mandate was in effect (see Table A1, column (3)).

$X_{e,j,t}$ is a vector of control variables that we include in the saturated specifications, e.g., to control for full or part-time jobs. The standard errors $\mu_{e,j,t}$ are clustered at the state-level (Bertrand et al., 2004).

[10] As mentioned, in the main specification we drop all counties with cities which passed city-level or county-level mandates but our findings are robust to keeping those treated counties. As mentioned in Section 2, one complication with the city-level mandates is that the city boundaries where the mandate applied rarely coincide with the county boundaries, which is why we elect to drop the entire county from the analysis.

Given the identification assumptions hold, Equation (1) estimates ϕ—the causal effect of mandated state sick pay on coverage, utilization, labor costs, and non-mandated benefits.

4.2 Event Study

We also estimate and visually illustrate event study models. To this end, we decompose the binary T_t time indicator in Equation (1) into a series of leads and lags around the effective date of each mandate (Schmidheiny and Siegloch, 2019). To do this, we construct indicators for five or more years through one year in advance of the state-level mandates ('leads', $\sum_{j=-5}^{-2} Lead_{s,j}$), the effective year of the mandate, and one through five or more years following the mandate ('lags', $\sum_{k=0}^{5} Lag_{s,k}$).[11] Doing so, we center the data around the mandate passage, with the March prior to passage as the reference year. We assign all localities without a mandate a zero for all lead and lag variables. Our event study equation is as follows:

$$y_{e,j,t} = \gamma_{e,j} + \delta_t + \kappa_j \sum_{j=-5}^{-2} Lead_{s,j} + \gamma_k \sum_{k=0}^{5} Lag_{s,k} + \rho X_{e,j,t} + \epsilon_{e,j,t} \tag{2}$$

The event study model offers to important extensions to the basic DD model. First, visual examination of the normalized pre-mandate trends (that is, the coefficient estimates on the lead indicator variables) allows us to test for and assess the plausibility of the common time trends assumption necessary for DD models to recover estimates of causal effects. Second, inclusion of the lag variables allow treatment effects to vary over time in the post-mandate years. Dynamics seem plausible in our context. For example, if employers are slow to comply with the mandated benefits or if employees require time to learn about their new benefits, allowing for dynamic treatment effects and differentiating between short- and medium-term effects may be crucial.

4.3 Identification

Because we rely on variation over one decade and across half a dozen U.S. states, as compared to the canonical DD setting with just one treatment and one comparison group, other policies contemporaneous to the treatments in all states inflicting a bias are much less likely to occur. Overall, we evaluate the average impact of the mandates for California, Connecticut,

[11] More specifically, the -5 indicator includes all years five or more years (in event-time) in advance of the effective date and the $+5$ indicator includes all years (in event-time) five or more years after the effective date.

Massachusetts, Oregon, and Vermont; that is, the mandates that were adopted at the state-level between March 2009 and March 2017. Washington D.C. adopted its mandate in the year prior to our study period (2008).

If mandates were a reaction to pre-existing trends in the outcome variables in the treated regions, we would identify such an endogenous implementation via our event study (that is, mandate leads that are statistically different from zero). Similarly, event studies have the power to provide evidence for anticipation effects.

The main remaining, and relatively weak, identification assumption is the absence of other confounding effects that are correlated with the staggered implementation of the sick pay mandates in all states over an entire decade. Specifically, the implementation of the mandates and the outcome variables must not be correlated with a systematic, third, unobservable driving force. Note that the mandates were implemented at different times of the year, in January as well July (Table A1), which adds to the credibility of the identifying assumption.

If the identification assumptions hold, Equations (1) and (2) identify internally valid causal mandate effects. The extent to which these estimates are externally valid for other U.S. states is difficult to assess. For such predictions, using estimates of regions whose labor markets are most similar to those in the state of interest is a promising approach. Our detailed heterogeneity analysis by industries, type of employer, and mandate specifics will provide additional guidance.

5 Results

We begin this section by estimating Equation (1). That is, we estimate DD models to elicit intent-to-treat (ITT) effects of the state-level mandates on a range of outcomes. We then supplement these average post-reform estimates with event studies. Event studies visualize how the effects have evolved over time and allow us to test for conditional parallel trends between the treatment and comparison groups. Next, we assess effect heterogeneity by stratifying the mean effects by type of job, occupation, and industry. Finally, we provide evidence for possible compensatory behavior by employers by estimating the impact of the mandates on non-mandated benefits such as paid vacation days.

5.1 Impact of the Mandates on Coverage Rates, Utilization and Labor Costs

DD Regression Models

Table 2 reports the results generated by Equation (1) for our main outcome variables. Each panel reports results from separate DD models that control for an increasingly larger set of covariates. Panel A includes year and employer fixed effects, whereas Panel B adds employee controls, Panel C adds employer-job fixed effects, and Panel D adds state-specific linear time trends. Overall, our results are highly robust across the various specifications.

[Insert Table 2 about here]

Coverage Rates. The four DD models in Column (1) of Table 2 show that, on average, state-level sick pay mandates increase coverage rates by 13 percentage points. Relative to the baseline coverage rate of 66%, the effects translate into an increase of 20%. Across all three specifications, the coefficient estimates are statistically significant at the 5% significance level .[12]

A reasonable question to ask is why coverage rates 'only' increased by 13 percentage point to 79% as opposed to 100%? Our sample includes only private sector employers for whom the mandates *should* be binding. In the following, we offer some explanations for this finding.

First, employers may not comply with the mandates. Moreover, Human Resources (HR) administrators (who provide the NCS benefit information) may be unaware of recently added benefits. While HR administrators *should* respond to the NCS survey, we cannot rule out the possibility that instead, at some employers, employees may complete the survey and may not be aware of the recently passed mandate and, in turn, their newly acquired benefits. Such unawareness has been documented in other related settings. For instance, Hall et al. (2018) find that 30% of all employees were unaware of the sick leave mandate in the first year in NYC.

Second, similar to non-compliance in case of minimum wage laws (Basu et al., 2010), deliberate non-compliance could limit benefit provision. On the other hand, employers respond to a government agency and could face penalties, e.g., administrative fines up to $4,000 in California, see for example Lexis Practice Advisor, 2017. However, as discussed in Section 2, in several states lawsuits are pending and it is likely that these mandate is not strictly enforced

[12]The BLS imputed values for sick pay coverage for roughly 30,000 observations. After dropping imputed observations the treatment effect on coverage increases by roughly two percentage points. Results are available upon request.

by the authorities. This unclear legal situation benefits non-compliant employers or those who are willfully ignorant.

Third, our classification of employers and mandates may include unavoidable errors. The NCS survey question is not specifically designed to evaluate sick pay mandates and hence does not perfectly mirror the details of the law in place in that state. That is, the survey question simply refers to paid sick leave coverage, but does not elicit additional details that would be relevant for whether the mandate is truly binding for the specific employer and employee. As an example, in Connecticut, the amendment provides relief to employers that experience seasonal or transitional fluctuations in their workforce. Consequently, because questionnaires are filled out at the employer-job level, even though employees in a non-small employer should be covered, an actual employee may not covered at the time of the survey.

Finally, although our study period extends to 2017 with only a few post-reform years for most laws, coverage rates may further increase over time. For example, in California, Massachusetts, and Oregon our data include just two post-reform years. In any case, we consider it precisely one contribution of this research to inform policymakers and researchers about the *de facto* increase in coverage as a result of government mandates, as measured by the best available data.

Utilization. Columns (2) and (3) of Table 2 show the estimated effects on paid and unpaid sick leave hours taken in the last 12 months (recall that we use the March responses of the NCS, so this refers to April of the year before until March of the survey year). As seen in column (2), there is robust evidence that, on average, paid sick leave taken increases by approximately two hours per year, which corresponds to an 11% increase relative to the baseline. Scaling this average effect by the 13 percentage point increase in coverage rates (column (1)) yields 15.4 hours or approximately two additional sick days taken per year.

Equivalently, the number of unpaid sick hours taken almost doubled to 0.9 (column (3)), which yields a scaled effect of 3.5 hours or roughly half of an eight hour work day. Recall that many employees also gain the right to take unpaid leave as a result of the mandates. Jorgensen and Appelbaum (2014) report that in 2012, almost half the U.S. workforce has not been eligible for FMLA (also see Section 2).

Labor Costs. Columns (4) and (5) of Table 2 show the estimated effects on associated employer labor costs. Labor costs are important to assess in this context because mandate critics commonly cite rising labor costs and depressed labor demand as reasons against government mandated sick pay (Kruth, 2018). However, using the Quarterly Census of Employment and Wages, Pichler and Ziebarth (2020) do not find evidence that wages and employment decreased by more than 2% as a result of the mandates at the county level. Columns (4) and (5) provide a possible explanation for this null finding. In the NCS, we find that mandates increase total sick leave costs by 10% (column (4), Panel D) to $610 per job and year; however, the costs per hour worked only increase by 2.7 cents (column (5), Panel D). Scaling this hourly cost increase by the 13 percentage point increase in coverage rates, costs increase by 'only' 21 cents per hour for the marginal employer.

We note that this sick leave cost estimate is a static calculation. In particular, the calculation does not consider possible changes in work productivity attributable to the mandate. For instance, overall work productivity could increase because employees can, post-mandate, recover from their sickness, work moral among employees increases, or employees (over-) compensate for lost labor after their sick leave. On the other hand, shirking and a lower work morale among employees who are not on sick leave (and therefore must cover for their coworkers who are out on leave) could reduce productivity. Moreover, we are not able to calculate potential costs to the employer for replacing an employee who is on sick leave.

While the labor cost estimate do not consider changes in productivity, it implicitly considers that reduced presenteeism behavior could reduce infections and thus sick leave taken by coworkers (cf. Pichler and Ziebarth, 2017). That is because labor costs are the product of actual sick leave taken and hourly wages (Section 3.1). If total sick hours taken decrease in some employers or occupations as a result of less presenteeism behavior and fewer infections, our labor cost estimate implicitly considers such an effect.

Event Studies

Figure 1 a to d plot events studies for the same four outcome variables estimated by Equation (2). This specification replaces the post-mandate dummy T_t with $\kappa_j \sum_{j=-5}^{-2} Lead_{s,j} + \gamma_k \sum_{k=0}^{5} Lag_{s,k}$. The March before the mandate's enactment is our reference period. The x-axis of Figure 1 shows the normalized time dimension for all treatment states. The y-axis shows the treatment effect in natural units.

All four event studies confirm the findings in Table 2 and additionally illustrate how the treatment effects evolve over time. Further, by examining the mandate leads, the event studies allow us to asses the credibility of our main identification assumption. As seen, differential trends between the treatment and control groups are largely absent; the pre-mandate coefficient estimates are small in magnitude and the gray confidence bands surrounding these estimates entirely cover the zero line on the y-axis.

[Insert Figure 1 about here]

Figure 1a documents a substantial increase in sick pay coverage rates in the year of the mandate's adoption; for example, in Oregon, where the law became effective January 1^{st}, 2016, $\gamma = 0$ refers to the survey as of March 2016. In the first post-mandate year, $\gamma = 1$, coverage rates further increase to roughly 18 percentage points and then remain at this level for the next four years, that is, through $\gamma_k \sum_{k=0}^{5} Lag_{s,k}$. This dynamic pattern of mandate effects is important. In particular, this pattern suggests large increases in coverage during the first two years post-mandate, but no further increases in the following years. Put differently, the medium-term effects appear to equal the short-term effects.

Figure 1b shows the dynamic effects on actual utilization of paid sick leave. As seen, there appears to be a small downward trend in utilization in the years before the mandates are effective. However, when omitting state time trends, as seen in Figure B1b (Appendix), this minor pre-mandate trend entirely vanishes. (This same pattern holds for the events studies on costs per hour (Figures 1d vs. B1d).) After the mandates' implementation, sick leave utilization increases from year one. In subsequent years, we observe further increases in sick leave utilization although statistical power decreases due to few states being observed for more than two post-mandate years (see Table A1). The increase in paid sick leave utilization over time is plausible as employees earn and accumulate sick leave credit over time. As additional NCS data become available, tracking the long-term utilization effects and assessing when the increase fades out will be very important for understanding the long-term policy effects.

Figure 1c (with state-specific linear time trends) and Figure B1c (without state-specific linear time trends) show the event studies for unpaid sick leave hours taken. Again, we observe nonlinear dynamic effects that are in line with our priors. First, in both figures, we do not observe substantial evidence for pre-mandate trends. The pre-mandate coefficeint estimates are close to zero in size and the 95% confidence intervals generally overlap with the zero line. After employees working for employers with less than 50 employees gained the right to take unpaid sick days,[13] however, we observe increases in sick leave utilization in the first two post-mandate years. Then, the likelihood to take unpaid sick hours start to decline again and revert back to the zero line in the fourth post-mandate year. This nonlinear effect is plausibly a function of how the sick pay mandates are designed—employees must first earn paid sick leave credit by working for an employer. Hence, initially employees primarily take unpaid sick hours. Once they accrue sufficient paid sick hours over time, employees increasingly take *paid* sick time, and unpaid sick time taken decreases again. This nonlinear pattern suggests that the medium-term effect of the mandates on unpaid sick leave utilization is likely not different from zero.

Finally, Figure 1d and Figure B1d (without state time trends) show the event studies for sick leave costs per hour worked. In both cases, we do not observe substantial trending in pre-treatment years. We observe increases in labor costs once employees begin to take paid sick time. This pattern is again in line with our priors as sick leave costs are simply the product of paid sick hours taken and the hourly wage.

Heterogeneity in Mandate Effects

We next explore effect heterogeneity in mandate effects by type of job and employer. Mirroring the large inequalities across employers and employees in the unregulated pre-mandate era (Susser and Ziebarth, 2016), one would hypothesize that heterogeneity in treatment effects should be large as well. In other words, we expect the mandates to have more bite in part-time and low-wage employers where coverage was particularly low in pre-reform years.

To this end, we re-estimate an augmented version of Equation (1) by estimating triple difference models. Specifically, we construct a triple interaction term $D_s \times T_t \times covariate$ and add this variable to Equation (1) along with the additional associated two-way interactions, $T_t \times covariate$ and $D_s \times covariate$. For readability, we report only the triple interaction terms; all other terms are available upon request.

[Insert Table 3 about here]

[13]Employees in bigger firms have been covered by FMLA also prior to the mandates.

Table 3 reports results from heterogeneity analyses. In particular, we test whether the treatment effects differ by full-time vs. part-time jobs (Panel A), union vs. non-union jobs (Panel B), and large (Panel C) vs. small (Panel D) employers. Focusing on the triple interaction term in column (1), the increase in coverage is larger in part-time (vs. full-time) jobs, non-unionized (vs. unionized) jobs, and small (vs. large) employers. The differential effects displayed are generally in line with our priors above.

The findings for use of paid and unpaid sick leave largely follow the pattern of the coverage rates, although there are some notable exceptions. For example, not surprisingly, employees working for employers with fewer than 50 employees experience a larger increase in utilization as a result of the mandates (columns (2) and (3), Panel D). However, for full- vs. part-time employees, we do not find statistically significant differences. We hypothesize that the larger coverage increase for part-time employees is counteracted by fewer opportunities of these employees to take sick days due to, among other factors, fewer work hours.

A similar countervailing force likely operates for the labor cost changes in columns (4) and (5): Because wages in small employer jobs and non-unionized jobs are lower, we find no significant differences in labor cost effects between large and small employers as well as unionized and non-unionized jobs—although the former job-types experience much larger coverage rate increases. An alternative explanation is that employees working for small employers and in non-unionized jobs are less likely to be aware of their rights (Hall et al., 2018), or are less likely to take sick days out of concern that it may trigger negative job consequences (Shapiro and Stiglitz, 1974; Ziebarth and Karlsson, 2014).

[Insert Figure 2 about here]

Figure 2 graphically illustrates effect heterogeneity for coverage effects by industry and occupation. The dark dots report the baseline coverage rates, whereas the lighter diamonds show the post-mandate coverage rates (baseline + treatment effect). Mirroring inequality in the U.S. labor market, we find substantial job inequality in baseline coverage rates as well as reform effect heterogeneity. For example, pre-mandate coverage rates are particularly low in the accommodation and food services industry (27%, Table B1) as well as in the construction industry (42%, Table B1). These industries also experience the largest increase in coverage rates through the mandates and show post-mandate coverage rates of 45% (accommodation and food) and 62% (construction) respectively.

All exact effect heterogeneity coefficient estimates for all industries and all occupations and all estimates for the other three outcome measures are in Table 4. They largely follow the pattern just discussed , see also Table 3 and Figure 2. In conclusion, the state-level sick pay mandates significantly and substantially decrease the widespread inequality in paid sick leave access and use in the U.S. labor market.

Aggregating to the County and State Level and Further Robustness Checks

Finally, we aggregate our data (1) at the county-level (Table B2, Appendix) as well as (2) at the state-level (Table B3, Appendix). Aggregating to a higher geographic unit allows us to implicitly test whether any systematic spillover effects exist. Aggregating in this manner also allows us to test whether there are any spillover or general equilibrium effects that could influence (either enhancing or muting) any of the mandate effects at the employer-job-level. If the results across the micro and aggregated data are equal, such effects are unlikely to play a major role. As observed for all five outcomes and all three model specifications in both tables, the results with aggregate data are very similar to our earlier results.

Further, in Tables B4 to B6, we conduction additional falsification tests. For example, while we have coded employers below mandate thresholds as not treated in states that exempt small employers, Table B4 now entirely drops these observations. Tables B5 and B6, by contrast, replicates the effect heterogeneity tables without including state time trends.

Placebo Estimates. Next, Figure 3 shows placebo regression estimates for our four main outcome variables. The placebo estimates correspond to the model in Panel D of Table 2. Estimates without state trends are in Figure B2 (Appendix). We produce these figures by first excluding treatment states from our data and then randomly assigning pseudo treatment states and times to the remaining data points. Then we re-estimate the model in Equation (1). We repeat this process 200 times and plot the resulting treatment effects on our main outcome variables in Figure 3a to 3d. The histograms show the results, with each treatment effect equal to one observation. The dashed lines represent the 5^{th} and 95^{th} percentile of the distribution of treatment effects. Finally, we add the true estimated treatment effect for comparison as black line. As seen, the true treatment effects are always clear outliers outside the 95% confidence interval, providing further evidence that they are not driven by confounding trends.

Decomposing Treatment Effects. Finally, we use insight from Goodman-Bacon (2018) in order to learn more about the underlying variation of our main results. In his contribution, Goodman-Bacon (2018) decomposes treatment effects in DD models with multiple treatments at different times into multiple, weighted, two-by-two DD estimators.

In order to perform the Goodman-Bacon decomposition using our data, we have to aggregate them to the state level and adjust our treatment variable to make it binary (at the state level).[14] Next, we re-estimate our main results and decompose them using the estimation command provided by Goodman-Bacon et al. (2019).

The results are in Table 5. We find that the estimated treatment effect is comparable but slightly smaller than the results in Panel B of Table B3 in the Appendix, where we also aggregate at state level. With regard to the decomposition, the two-by-two DD estimate compares workers at employers in states that mandated benefits between 2009 and 2017W with workers that were never treated ('Never_v_timing'). This element receives more than 96% of the total weight. The resulting treatment effect is thus very similar to the overall treatment effect. Furthermore, comparing workers in states that mandated sick pay earlier as compared to later ('Timing_groups') yields a slightly larger treatment effect—however, this element receives only 2% of the weight. Finally, the within variation has a very low weight of less than 1% implying that our results are not driven by whether we include controls or not.

5.2 Impact on Non-Mandated Benefits, Hours Worked, and Type of Sick Plan

Tables 6 and 7 report DD estimates for different components of employee compensation. These additional benefits are plausibly valuable to employees, but costly to employers and not mandated. Hence these benefits could be curtailed to offset increased sick leave costs attributable to the mandates we study. In these auxiliary analyses, we thus test for unintended compensatory and spillover effects of sick leave mandates.

Crowding-Out of Non-Mandated Benefits

Columns (1) to (7) of Table 6 test for substitution or crowding-out effects of non-mandated benefits. In particular, the estimates capture the effect of the mandates on the provision of

[14] As some state mandates have firm size exemptions, aggregating to the state level leads to a non-binary treatment (for more details on the laws see Table A1). In order to decompose our treatment effect, a binary treatment variable in required.

(1) health insurance, (2) prescription drugs, (3) dental insurance, (4) life insurance, (5) short-term disability insurance, (6) long-term disability insurance, and (7) parental leave benefits. Broadly, we observe no evidence that sick leave mandates affect any of these outcomes. Indeed, the coefficient estimates are small in magnitude (and imprecise); further, the estimates carry alternating signs which do not imply any clear pattern in benefit provision post-mandate. An exception to this pattern is health insurance: provision of this benefit may decline post-mandate according to the point estimate, although the coefficients are quite small in size. Importantly, however, the event study shows no systematic decrease health insurance provision as a result of the sick pay mandates (Figures B3a and b, Appendix).

Next, Columns (1) to (3) of Table 7 test whether annual vacation hours, national holiday hours, and overtime hours are affected by the mandates. Again, all coefficient estimates are small in size relative to the baseline mean. Moreover, none of the eight coefficient estimates on vacation and overtime hours are statistically different from zero. Only the estimates for annual national holiday hours are negative and statistically significant, although our preferred estimated in Panel D, column (2) is only 1.4% of the mean. However, as above in the case of health insurance, the event studies in Figures B3c and d (Appendix) let us conclude that there is no evidence of a systematic crowd-out of holiday hours provided by employers.

[Insert Table 6 and 7 about here]

Annual Hours Worked and Paid

Columns (4) to (6) of Table 7 test for mandate-induced changes in (4) hours worked per year, (5) hours of overall paid leave per year, and (6) hours paid per year. Hours of paid leave per year includes all forms of paid leave such as paid sick days, parental leave, elder-care, paid vacation, and paid national holidays.

First, we find no statistically significant evidence that sick pay mandates affected hours worked. The coefficient estimates in column (4) have alternating signs and are small, relative to the mean. For example, in Panel C, the coefficient estimate is positive and equals 0.02% of the mean but is not statistically distinguishable from zero. Likewise, column (5) provides little evidence that the annual number of hours paid change substantially in post-mandate years. However, the coefficient estimates for the annual number of hours on paid leave are marginally significant and 0.9% of the mean (column (6)). These positive increases are in line with, and likely the result of, the increased utilization of sick days.

Wages and other benefits

Columns (7) to (9) of Table 7 test for changes in wages (7), employer costs for health insurance (8), and non-production benefits (9). Our results suggest that while health insurance and non-production benefits are unaffected by the mandates, wages may slightly increase with sick pay. However, again and as above, the event studies (Figures B3e and f, Appendix) do not support any systematic wage increase. Similar results are also found in Pichler and Ziebarth (2020).

Type of Sick Leave Plan

Finally, we investigate whether sick pay mandates alter the type of plan offered to employees. Columns (8) and (9) of Table 6 test for whether the mandates affect the propensity that employers offer 'fixed' sick leave plans (column (8)) or 'consolidated' sick leave plans (column (9)).

Table 1 shows that 16% of all employer-job observations come with the benefit of a consolidated leave plan. These are also called consolidated 'Paid-Time-Off' (PTO) plans and have become increasingly popular in the U.S. Under a PTO plan, employers do not provide a *separate* number of days for sick leave, vacation, or parental leave, but instead aggregate or 'consolidate' the total number of paid leave days per year, independent of reason (Lindemann and Miller, 2012). For instance, the BLS reports that the average consolidated PTO plan has accumulated 19 days of available paid leave after five years of service with the employer (Bureau of Labor Statistics, 2018a). Paid sick leave mandates are in compliance with such PTO plans as long as they are as least as generous as the sick leave accounts required by the law (ADP, 2016).

However, as a result of the mandate, column (8) clearly shows an increase in the share of jobs with *separate* sick leave plans. The increase is 14 percentage points and nearly identical to the main coverage increase in column (1) of Table 2. The likelihood that employers offer a PTO plan either decreases slightly by 1.7 percentage points (column (9), Panels A and B) or does not appreciably change (column (7), Panel D). In conclusion, columns (8) and (9) imply that sick pay mandates overwhelmingly induce employers to set up separate sick leave plans, as intended, likely to avoid uncertainty whether their consolidated PTO plan would comply with the law (Miller, 2015).

6 Optimal Sick Pay and Welfare Effects

This section develops a model of optimal sick pay to evaluate the welfare effects of mandating sick pay. Our intention is not to explain *why* coverage rates are highly unequal across types of jobs and *why* private insurance markets for short-term sick leave policies are very limited in the U.S. (cf. Hendren, 2013, 2017, for similar analyses related to health insurance), despite clear evidence that employees highly value sick pay (cf. National Paid Sick Days Study, 2010; Maestas et al., 2018). Rather, as in the Baily-Chetty framework following Baily (1978), Chetty (2006) and Chetty and Finkelstein (2013), we will use the model to derive sufficient statistics. Unlike Baily-Chetty, however, we do not assess optimal unemployment benefits but instead optimal sick pay leave. Without the need to estimate model parameters, this setup allows us to use the estimated elasticities of the previous section to derive welfare implications, similar to the case of unemployment insurance (cf. Chetty, 2008).

Our ultimate goal is to assess whether increasing access to paid sick leave through government mandates is welfare improving or not. In other words, we will examine whether the voluntary provision of sick pay by employers—as it is currently still the case in the majority of U.S. states—leads to an underprovision of sick pay, and whether the optimal level of sick pay would be higher.

6.1 Model Setup

Our model is a one period model. The model considers both employee utility and employer profits. The social planner maximizes the sum of both and thus overall welfare.

Employees

Representative employees maximize their utility u, which is a function of their sickness level σ, their consumption c, and their leisure time l. Hence their utility function is $u(\sigma, c, l)$.

The sickness level σ is continuous and bounded between zero and one. σ is zero when the employee is perfectly healthy and positive when the she is sick, the latter occurring with probability p. Sickness has a density $f(\sigma)$ and a cumulative distribution $F(\sigma)$.

Employees consume their income earned from working, which is w when they work and αw (with $\alpha \,\epsilon\, [0,1]$) when they are on sick leave. Note that we study the implementation of U.S. sick pay mandates, which provide sick pay at a replacement rate of 100% *for the amount of sick hours accumulated*. Although this case slightly differs from the standard social insurance framework, one can normalize and rewrite the actual sick pay level as a standard $\alpha \,\epsilon\, [0,1]$ case.[15]

With h representing contracted work hours and T total time, leisure time equals $l = T - h$ when employees work and $l = T$ when they are on sick leave. Moreover, utility decreases in sickness, but increases in consumption and leisure over the whole domain. Finally, we assume that leisure time is more valuable when sick ($\frac{\partial^2 u}{\partial\sigma\partial l} > 0$), whereas consumption is less valuable when sick ($\frac{\partial^2 u}{\partial\sigma\partial c} \leq 0$), see Finkelstein et al. (2013) for empirical evidence on the latter.

Given these model parameters, we define the utility differential between work and sick leave as $\triangle = u(\sigma, w, T-h) - u(\sigma, \alpha w, T)$. If $\triangle$ is positive, employees will work; otherwise, they will call in sick and take sick leave. Setting $\triangle = 0$ gives a unique indifference level of sickness σ^*_α for a given replacement rate α.

Summing up, at the population-level, total employee utility is:

$$U = (1-p)u(0, w, T-h) + p\int_0^{\sigma^*_\alpha} f(\sigma)u(\sigma, w, T-h)d\sigma$$
$$+p\int_{\sigma^*_\alpha}^1 f(\sigma)u(\sigma, \alpha w, T)d\sigma. \tag{3}$$

The first term represents utility for healthy employees who work with $\sigma = 0$. The second term represents utility for sick employees who work ('presenteeism'); and the last term represents utility for sick employees on sick leave.

Next, Equation (4) shows how a change in sick pay α affects total employee utility:

[15] For newly covered employees who have accumulated sufficient sick pay credit, mandates imply an increase in α from zero to one. For newly covered employees who cannot cover their sick leave needs with the available credit, mandates imply an increase in α from zero to (sick hours accumulated/sick hours needed). At the population level, the mandates imply an increase in the weighted average α of employees who had sick pay before the reform, and employees who gained access through the reform. In the welfare analysis, we will use this population-level interpretation and causal changes in population coverage rates as empirical inputs for α.

$$\frac{dU}{d\alpha} = pw \int_{\sigma^*_\alpha}^{1} f(\sigma) u'_c(\sigma, \alpha w, T) d\sigma > 0. \tag{4}$$

Because of the envelope theorem, all other behavioral adjustments have no effect on total employee utility. For instance, the labor supply reaction ('moral hazard') does not impact total employee utility. Put differently, employees will call in sick more often because of more generous sick pay, $\frac{\partial \sigma^*_\alpha}{\partial \alpha} < 0$.

Employers

Representative employers cannot observe employee sickness σ.[16] Moreover, employees with sickness level σ have work productivity $\pi(\sigma)$ with $\pi'(\sigma) < 0$, which is also unobservable. In other words, sickness causes employees to be less productive. Given σ^*_α and normalizing the workforce to unity, total employer profits are then:

$$\Pi = (1-p)(\pi(0) - w) + p \int_0^{\sigma^*_\alpha} f(\sigma)(\pi(\sigma) - w) d\sigma - p\alpha w \int_{\sigma^*_\alpha}^{1} f(\sigma) d\sigma. \tag{5}$$

The first term represents profits generated by healthy employees who work. The second term represents profits generated by sick employees who work. Because of their sickness, sick employees have lower productivity than healthy employees, but still earn wage w. The last term represents profits—or rather losses—generated by employees on sick leave, $p \int_{\sigma^*_\alpha}^{1} f(\sigma) d\sigma$ who obtain sick pay αw, while not participating in production.

Following Chetty (2006), we assume that wages are exogenously given, in the sense that employers pay market wages w. That is, approximating reality, we assume rigid wages and only partially observable productivity. Otherwise, the employer's optimization problem would be trivial: they would simply pay employees according to their daily productivity. In our model, employers can only optimize over sick pay generosity αw. Equation (6) shows how a change in α affects employer profits:

[16] We note that in reality sickness is partially observable at best. First, sickness may not result in physical and observable symptoms. Second, over-the-counter medications that suppress sickness symptoms, e.g. coughing and nasal congestion, are widely available (Earn et al., 2014).

$$\frac{\partial \Pi}{\partial \alpha} = p\frac{\partial \sigma_\alpha^*}{\partial \alpha} f(\sigma_\alpha^*)(\pi(\sigma_\alpha^*) - w) + p\frac{\partial \sigma_\alpha^*}{\partial \alpha} f(\sigma_\alpha^*)\alpha w - pw\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma. \tag{6}$$

When the employer provides more generous sick pay, several changes occur. First, fewer employees work when sick. As seen in the first term of Equation (6), depending on the profitability of the marginal employee, the effect on profits might be positive or negative. Second, more employees are on sick leave and the employer provides sick pay to more employees (see the second term of Equation (6)). Third, total employer sick pay costs rise because of the increase in generosity α (see the third term of Equation (6)).

For the employer, sick pay is optimal when it incentivizes unproductive employees to call in sick and receive αw instead of w; that is, employees with $\pi(\tilde{\sigma}) < w$. Or, mathematically, the second term and the third term of Equation (6) will always be negative.[17] Hence the employer will only increase sick pay if the first term is positive and sufficiently large.

The employer will provide more sick pay if, under current sick pay levels, too many sick employees work and have productivity less than their wage. More generous sick pay will then incentivize those unprofitable employees to call in sick, but require the employer to provide more generous sick pay, and more generous sick pay to more employees. Under optimal sick pay for the employer, all three factors in Equation (6) will sum to zero.

Rearranging Equation (6) yields:

$$\frac{\partial \Pi}{\partial \alpha} = p\frac{\partial \sigma_\alpha^*}{\partial \alpha} f(\sigma_\alpha^*)(\pi(\sigma_\alpha^*) - (1-\alpha)w) - p\int_{\sigma_\alpha^*}^1 f(\sigma)w d\sigma. \tag{7}$$

Social Planner and Optimal Sick Pay

The social planner maximizes total welfare. We assume that total welfare is simply the sum of total employee utility (Equation (1)) and total employer profits (Equation (5)):[18]

[17] The second term is negative because of $\frac{\partial \sigma_\alpha^*}{\partial \alpha} < 0$

[18] Altering the shares and overweighting employees or employers is straightforward.

$$
\begin{aligned}
W &= (1-p)u(0, A+w, T-h) + p\int_0^{\sigma_\alpha^*} f(\sigma)u(\sigma, A+w, T-h)d\sigma \\
&+ \int_{\sigma_\alpha^*}^1 f(\sigma)u(\sigma, A+\alpha w, T)d\sigma \\
&+(1-p)(\pi(0)-w) + p\int_0^{\sigma_\alpha^*} f(\sigma)(\pi(\sigma)-w)d\sigma - p\int_{\sigma_\alpha^*}^1 f(\sigma)\alpha w d\sigma. \qquad (8)
\end{aligned}
$$

The social planner varies sick pay generosity in order to maximize total welfare such that:

$$
\begin{aligned}
\frac{dW}{d\alpha} &= \frac{dU}{d\alpha} + \frac{\partial \Pi}{\partial \alpha} \\
&= pw\int_{\sigma_\alpha^*}^1 f(\sigma)u_c'(\sigma, \alpha w, T)d\sigma \\
&\quad + p\frac{\partial \sigma_\alpha^*}{\partial \alpha} f(\sigma_\alpha^*)(\pi(\sigma_\alpha^*) - (1-\alpha)w) - p\int_{\sigma_\alpha^*}^1 f(\sigma) w d\sigma. \qquad (9)
\end{aligned}
$$

Thus, the social planner considers the cost and benefits of more generous sick pay for both employees and employers. The second part of Equation (9) is the same as Equation (7) and shows how varying sick pay affects employer profits.

The first part of Equation (9) is the same as Equation (4) and shows how varying sick pay affects employee utility. More generous sick pay reduces labor supply and fewer employees will work. However, employees who work will be healthier. Overall, more generous sick pay is beneficial for employees. Therefore, as long as the social planner considers employee utility in her overall welfare function, the social planner will choose a higher level of optimal sick pay than the profit maximizing employer.

When rearranging Equation (9), we obtain the welfare maximizing optimality condition, under which both sides of Equation (10) are equal:

$$
\frac{w\int_{\sigma_\alpha^*}^1 f(\sigma)(u_c'(\sigma, \alpha w, T) - 1)d\sigma}{\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma} = \varepsilon \frac{\pi(\sigma_\alpha^*) - (1-\alpha)w}{\alpha}. \qquad (10)
$$

where the left-hand side (LHS) is the difference between marginal employee benefits (higher consumption utility) and marginal employer costs (higher sick pay), normalized by the share of sick employees. The right-hand side (RHS) is the difference between employee productivity when working sick ('presenteeism') and the difference between the wage and sick pay, weighted by the labor supply elasticity ε.[19]

Essentially, the social planner would increase sick pay as long as (1) the increase in marginal employee utility (because of the higher marginal consumption utility) exceeds marginal employer costs, *and* until this differential equals (2) the differential between the lower productivity when working sick, and the difference between sick pay and wages.

Equation (10) is similar to the standard Baily-Chetty formula (Baily, 1978; Chetty and Finkelstein, 2013), but there are some notable differences. First, in the standard Baily-Chetty framework, employees pay for their own welfare benefits through higher taxes. This phenomena results in the balancing of marginal utilities in different states (low and high taxes). Our setting is different because the employer provides sick pay; the social planner trades-off how much employees value more sick pay against the employer costs of providing the benefit.

Second, sickness is a continuous state and affects work productivity. Hence, for the employer, the provision of some sick pay is optimal because it incentivizes sick and unproductive employees (who are, at least partially, unobservable for the employer) to call in sick and take the lower sick pay, not the higher salary. However, because employers maximize profits and not employee utility, optimal employer sick pay will always be lower than welfare optimizing sick pay.

(Note that, to keep the model tractable, we abstain from negative externalities due to infections at the workplace, see Pichler and Ziebarth, 2017.)

6.2 Welfare Effects of Mandating Sick Pay

Whether sick pay mandates increase welfare depends on Equation (10) and the empirical sufficient statistics from the previous section. Under optimal sick pay, both sides of Equation (10) are identical. The LHS is the difference between higher marginal employee utility and higher marginal employer costs as a result of more sick pay, weighted by the share of employees on sick leave. The RHS is the effect of more sick pay on employer production and wage payments,

[19] $\varepsilon = \frac{\partial \int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma}{\partial \alpha} \frac{\alpha}{\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma} = -\frac{\partial \sigma_\alpha^*}{\partial \alpha} f(\sigma_\alpha^*) \frac{\alpha}{\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma}$

weighted by the labor supply elasticity ε. When substituting λ and δ we can write Equation (10) as:[20]

$$w\lambda \gtreqless \varepsilon \frac{w\delta - (1-\alpha)w}{\alpha}. \tag{11}$$

Next we incorporate our empirical inputs from the previous section to calculate the RHS. First, the elasticity ε can be calculated from Table 1 and Table 2. We use the coefficient estimates in Table 2, Panel D, columns (2) and (3), indicating the causal effect of obtaining access to sick leave on sick hours taken (1.816 + 0.479 = 2.295) as a share of total hours paid (1838.1, Table 1). Then, we scale by the increase in the coverage rate $\partial\alpha = 0.128$ (Table 2, column (1)). Second, we multiply by the baseline coverage level $\alpha = 0.659$ (Table 2, column (1)) and also consider the baseline level of sick hours taken as a share of total hours worked (17.8 + 0.541= 18.341/1838.1, Table 2, columns (2) + (3)). We then obtain the elasticity ε as:

$$\varepsilon = \frac{\partial \int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma}{\partial\alpha} \frac{\alpha}{\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma} = -\frac{\partial\sigma_\alpha^*}{\partial\alpha} f(\sigma_\alpha^*) \frac{\alpha}{\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma} = \frac{2.295/1838.1}{0.128} \frac{0.659}{18.341/1838.1} = 0.644. \tag{12}$$

That is, when sick pay coverage rates increase by 1% at the population level, sick hours taken (as a share of total work time) increase by 0.64%.

In the RHS of Equation (11), δ indicates work productivity when sick, which is challenging to elicit. However, the American Working Conditions Survey (AWCS) asks a nationally representative sample of U.S. adults to estimate their reduced work productivity when working sick (Maestas et al., 2018). The estimate for the average employee is a reduction of 23%, which is why we use $\delta = 0.77$ as our baseline scenario.

When incorporating the remaining values for w and α, taken from Table 1, we obtain a RHS value of $0.644 \times \frac{(21.69 \times 0.77 - (1-0.659) \times 21.69)}{0.659} = 9.10$. Figure 4 graphically plots the RHS values as a solid black line and function of δ; the x-axis indicates all possible δ values, which we allow to vary as a sensitivity test. As seen, for $\delta = 0.77$, the sample average taken from the AWCS, we obtain a y-axis value of 9.10.

[20] We substitute λ assuming on average that $u_c'(.) - 1 = \lambda$ for the population share $\int_{\sigma_\alpha^*}^1 f(\sigma)d\sigma$. We also substitute $w\delta$ for $\pi(\sigma_\alpha^*)$ assuming that work productivity can be written as a multiplier of the wage.

[Insert Figure 4 about here]

The y-axis in Figure 4 indicates the LHS of Equation (11) for different values of λ. Recall that the LHS is the difference between the marginal increase in employee utility and the marginal employer costs when sick pay becomes more generous. As already noted by Summers (1989), this difference between the employee value of a mandated benefit and the employer cost of providing it should be fundamental in the social planner's decision whether or not to mandate benefits. If this difference is negative, the employer costs of the benefit exceed its value to the employee. In that case, mandating the benefit cannot be welfare improving. Sick pay is thus optimal when the differential is positive and equal to the RHS of Equation (11), as shown in Figure 4. As derived above, for $\delta = 0.77$, this will be the case if the LHS equals 9.10.

How can we determine λ and the LHS? We offer three approaches. First, there is suggestive evidence that employees place substantial value on sick pay. Recall that 75% of Americans support sick pay mandates and 69% consider this benefit 'very important' for them. Further, a clear majority of Americans considers sick leave a basic employee's right and believe that providing this benefit is more important than existing employees' rights such as the right to join a union (National Paid Sick Days Study, 2010).

Second, Figure 4 includes several gray horizontal lines for different LHS values, assuming a constant marginal utility. To test the robustness of our conclusions, we display several horizontal lines for $\lambda \in 0; 0.2; 0.4; 0.6; 0.8$. For a RHS value of 9.10, we find that λ must exceed 0.42 for mandating sick pay to be welfare improving. In other words, for our baseline scenario, the welfare model suggests that mandating sick pay is welfare improving as long as the marginal employee utility exceeds the marginal employer costs by 42% or more. Recall that our estimate of the increase in labor costs is about \$0.21 per hour worked for the marginal employer (Section 5.1 and Table 2, Panel D).

Finally, we refer to a recent study by Maestas et al. (2018) that experimentally elicits the willingness-to-pay (WTP) for ten PTO days among a representative sample of U.S. employees. The findings shows that the average WTP equals 15% of the annual gross wage. In fact, assuming 260 workdays per year, for an annual gross wage of \$50K, this WTP equals \$750 per day whereas the daily gross wage is only \$192. In any case, the elicited WTP value clearly exceeds even the largest possibly assumed LHS differential of 80% in Figure 4. If $\lambda = 0.8$, independent of the productivity when working sick, the LHS will always exceed the RHS in Figure 4 and more generous sick pay will always increase welfare.

In conclusion, if the true WTP of employees for more generous sick leave is anywhere close to the elicited WTP in Maestas et al. (2018), welfare will improve if more states mandate sick pay in the U.S. Specifically, based on our model of optimal sick pay and our causal labor supply estimates, this will be the case if marginal employees' valuation of gaining access to sick pay exceeds the employer costs of providing it by at least 42%.

A final note of caution almost always applies in such calculations, but is still worth mentioning. The empirical inputs for these welfare calculations stem from average coefficient estimates for several U.S. states and the first post-reform years. Considering effect heterogeneity, statistical uncertainty, and alternative economic conditions would naturally introduce wider bandwidths.

7 Discussion and Conclusion

This paper comprehensively evaluates the labor market and welfare effects of enacting sick pay mandates at the state level in the United States. In the first part of the paper, we estimate the effects of mandating sick pay on coverage, paid and unpaid sick leave utilization, labor costs, and non-mandated benefits. In particular, we leverage the experiences of several U.S. states with more than 70 million residents. For our empirical estimates, we use the National Compensation Survey (NCS) from 2009 to 2017, coupled with difference-in-differences and event study models which exploit the policy-induced variation in the implementation of the mandates across U.S. states and over the past decade. The NCS is a rich government dataset at the employer-job level specifically designed to measure and track labor compensation and costs.

Our findings address important gaps in the economics literature on labor market inequalities and employer mandates more broadly. The U.S. is a country with one of the least generous paid leave systems among all OECD countries (Adema et al., 2016; Raub et al., 2018). Federal minimum standards concerning paid vacation, paid parental leave, paid eldercare, and paid sick leave are largely absent, leading to large variation in the voluntary provision of such benefits by employers. In general, better paying jobs for higher educated employees tend to offer paid leave benefits, whereas part-time and low-income jobs for lower educated employees do not. An important open question is to what extent employer mandates are effective in providing and facilitating the provision and use of such benefits; or whether they have unintended consequences and lead to a reduction, and potentially inefficient reallocation, of non-mandated benefits (that employees may value). Other crucial questions are to what extent such mandates increase labor costs and depress employment and wage growth. Pichler and Ziebarth (2020) find no evidence that the U.S. sick pay mandates significantly affect employment and wages, or lower the growth rate of wages, by more than 2%.

This paper provides state-of-the-art empirical evidence on the overall effectiveness of sick pay mandates along several margins. It also provides a welfare analysis. To this end, we study the important 'first stage' effects of mandating sick pay on actual changes in sick pay coverage. Using government data we also estimate sick leave utilization effects, assess the relevance of mandates for labor costs, and estimate the extent to which employers respond to the mandates by curtailing other forms of compensation. We also develop a model of optimal sick pay and use the empirical inputs to assess whether mandating sick pay is welfare improving or not. Our research provides timely evidence on all these questions and contributes to a better understanding of how recent mandates function, which is relevant from both an economic and a policy perspective.

Our findings show a clear and significant increase in sick leave coverage rates of 13 percentage points (or 20% relative to the pre-treatment mean of 66%) in the four years following mandate passage. Interestingly, after an initial increase in coverage rates by 18 percentage points, we find no further increase in subsequent years. Further research should probe the persistent coverage gap that we document. Non-compliance and lack of awareness are both plausible explanations. For instance, Hall et al. (2018) report that, in New York City, only 30% of employees were aware of the new sick pay mandate in the first year after the implementation. However, more data-driven explanations of this finding are an important path for future work.

As expected, we also find a significant two hours increase in paid sick leave use following mandate implementation. Scaling this average increase by the share of marginal jobs that have been covered by the mandates suggests that newly covered employees take, on average, two additional sick days per calendar year. The implied elasticity is 0.64, meaning that the share of total work time spend on sick leave increases by 0.64% for every increase in the coverage rate by 1%. Further, we find that total sick leave costs increase by 10%, which translates to 21 cents per hour for marginal employers and represents 1% of the hourly wage. Moreover, we find limited evidence that employers curtail non-mandated benefits as a response to the mandates to reduce overall labor costs.

Finally, we develop a welfare model of optimal sick pay and generate several findings. First, the models shows that profit maximizing employers will also provide some level of sick pay in the absence of mandates. The intuition for this finding is that work productivity decreases when employees work sick. When wages clearly exceed the productivity of the working sick, sick pay incentives those employees to call in sick and take (the lower) sick pay instead. Second, the profit maximizing sick pay level of the employer falls short of the level that a social planner would set, because the social planner also considers employee utility. Third, for the social planner to mandate sick pay, (1) the employee utility of more generous sick pay has to exceed the employer costs of providing this benefit, and (2) this differential must be benchmarked with the effects of more sick pay on employer production, specifically the changes in productivity and wage payments, weighted by the labor supply elasticity. Finally, when plugging sample means and our estimated causal effects into our derived optimality condition, we find that mandating sick pay is welfare-improving in the U.S., as long as employees' valuation of the benefit exceeds the employer costs by 42%. Survey evidence as well as evidence of experimentally validated compensating wage differentials suggest that this is the case (National Paid Sick Days Study, 2010; Maestas et al., 2018). Moreover, this threshold is likely an upper bound as it does not consider reductions in infectious diseases as a result of reduced presenteeism behavior (Pichler and Ziebarth, 2017).

As cities and states will be implementing more sick pay mandates, more empirical evidence on the indented and unintended consequences of these mandates will become available. We look forward to fruitful discussions among social scientists.

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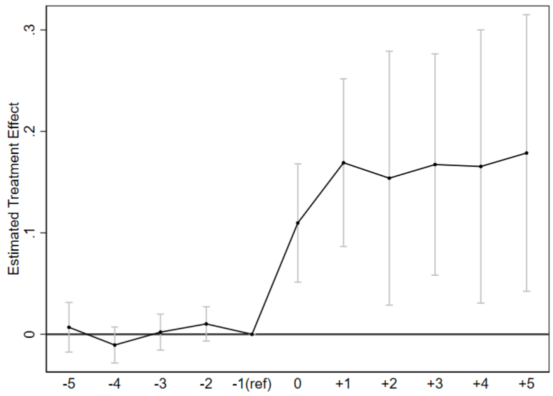
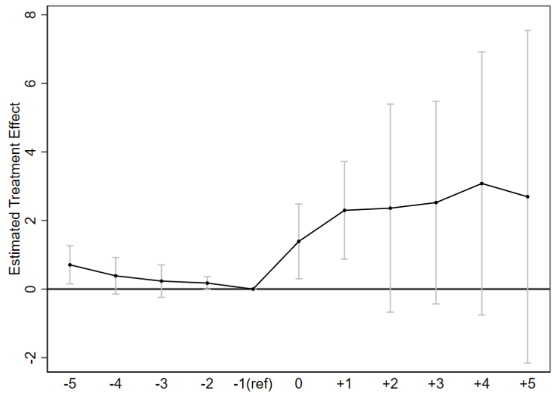
Figures and Tables

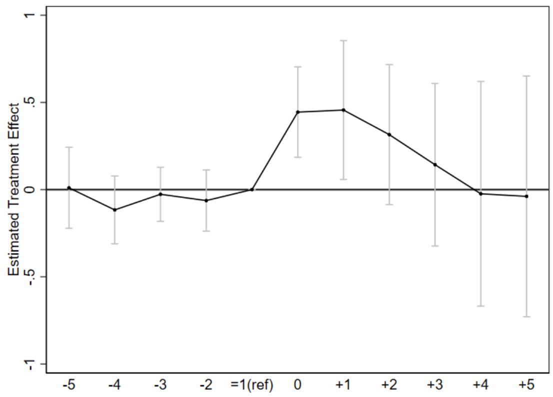
Figure 1: Event Studies from Difference-in-Differences Models



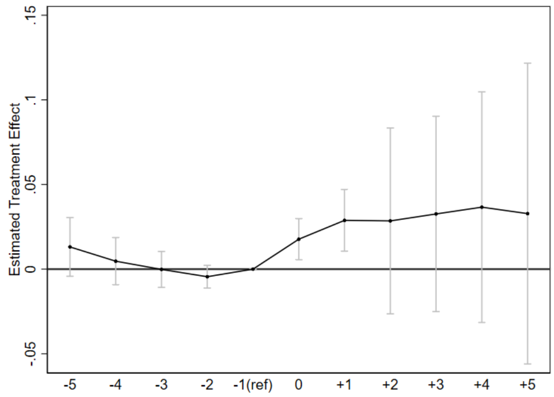
(a) Sick pay coverage



(b) Paid sick leave hours taken



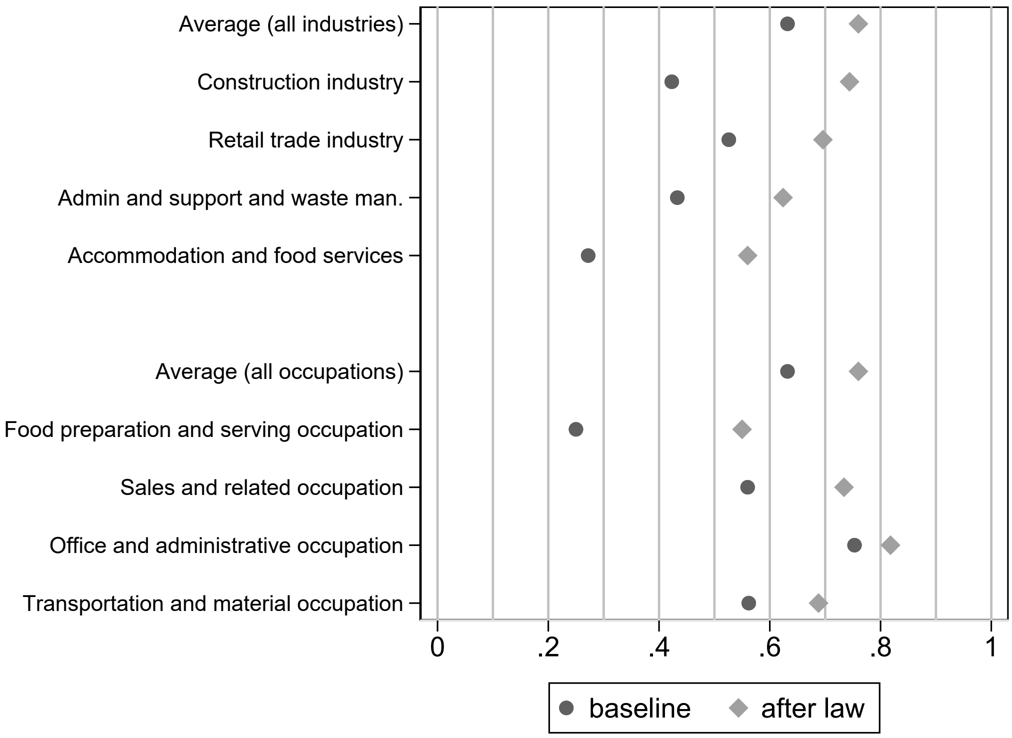
(c) Unpaid sick leave hours taken



(d) Sick leave costs per hour worked

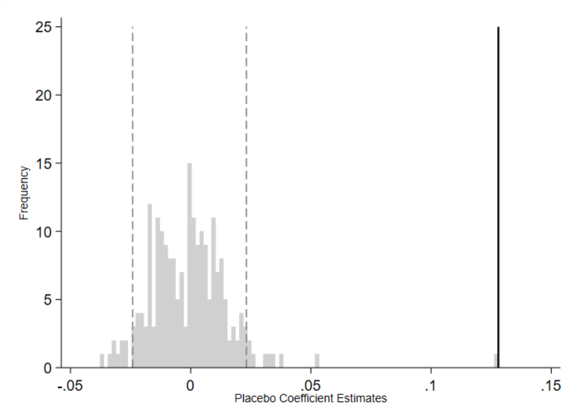
Notes: The graphs show event studies based on DD models as in Equation (2). All models include employer-job fixed effects, time fixed effects and state time trends (for event studies without trend see Figure B1). The errors terms are clustered at the state level and the gray bars depict 95% confidence intervals. The corresponding DD point estimates can be found in Panel D of Table 2. For more information about the sick pay reforms, see Table A1.

Figure 2: Coverage Effect Heterogeneity by Industry and Occupation

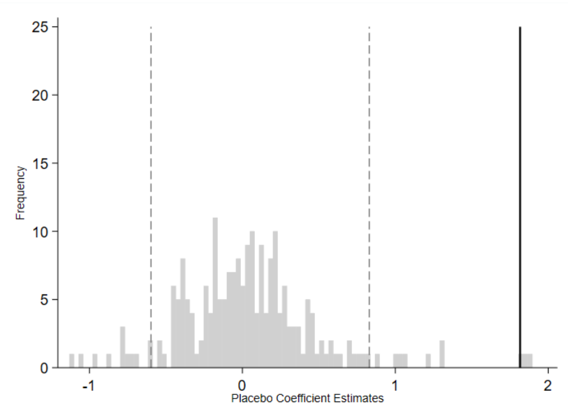


Results are for coverage only. Full results are in Table 4. Industries and occupations are sorted by the weighted frequency of the industries and occupations.

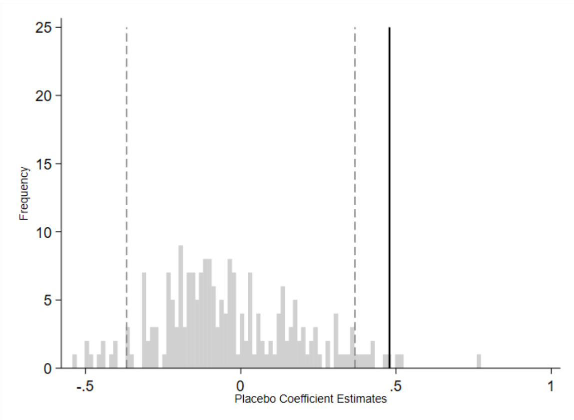
Figure 3: Placebo Regression Results



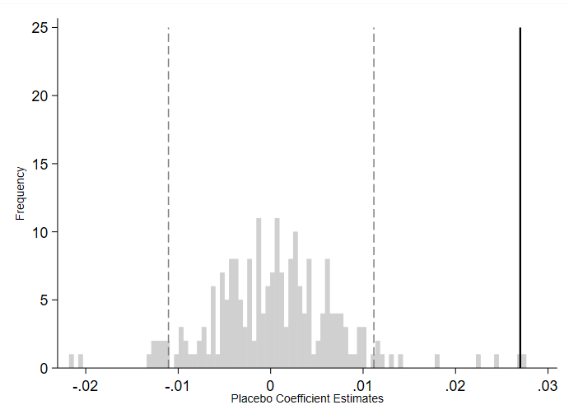
(a) Sick pay coverage (p=0.001)



(b) Paid sick leave hours taken (p=0.01)



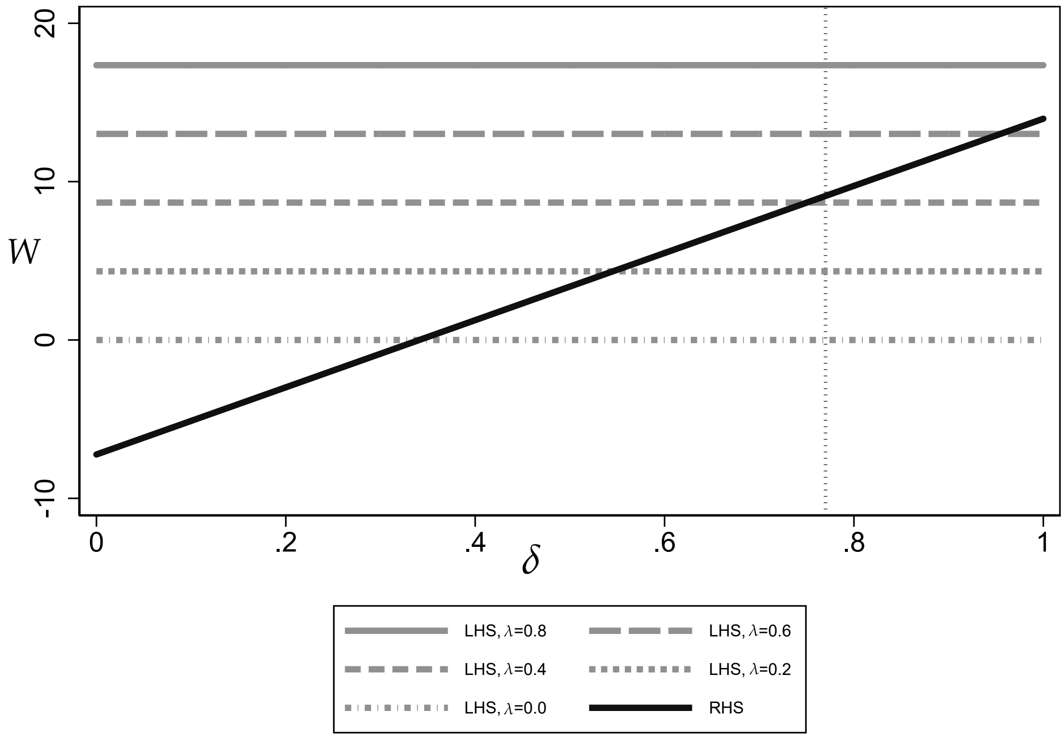
(c) Unpaid sick leave hours taken (p=0.05)



(d) Sick leave costs per hour worked (p=0.01)

Notes: This figure plots the distribution of the estimated placebo regressions (n=200) that excluded treatment states and randomly assigned pseudo treatment states, as compared to the true estimate. All models include employer-job fixed effects, year fixed effects and state time trends (for event studies without trend see Figure B2 in the Appendix). The vertical black line and corresponding bar denotes the true coefficient estimates. The p-values are displayed next to the variable name. The corresponding DD point estimates can be found in Panel D of Table 2. For more information about the sick pay reforms, see Table A1.

Figure 4: Welfare Effects of Sick Pay Mandates



Notes: The graph depicts the LHS and RHS of Equation (11) for different values of λ on the y-axis and δ on the x-axis. If the LHS exceeds the RHS of Equation (11), more generous sick pay is welfare improving.

Table 1: Descriptive Statistics, National Compensation Survey (NCS) 2009-2017 (weighted)

	Mean	Std. Dev.
Outcomes		
Sick leave offered (binary)	0.632	0.482
Paid sick hours taken (hours per year)	15.84	18.72
Unpaid sick hours taken (hours per year)	0.647	4.595
Sick leave costs total (in 2017 $)	448.5	792.5
Sick leave cost per hour worked (in 2017 $)	0.251	0.479
Other benefits and characteristics		
Full-time employment (binary)	0.739	0.439
Part-time employment (binary)	0.261	0.439
Unionized (binary)	0.086	0.281
Hourly wage (in 2017 $)	21.69	18.42
Hourly health insurance cost (in 2017 $)	2.403	2.427
Hourly non-production bonus (in 2017 $)	0.656	5.619
Paid vacation hours per year	69.58	57.57
Paid national holiday hours per year	44.11	32.91
Paid overtime hours per year	57.2	106.2
Annual hours worked	1700	469
Annual hours paid leave	138	102
Annual hours paid (=sum of worked and leave)	1838	523
Health insurance offered (binary)	0.688	0.464
Presc. drug insurance offered (binary)	0.673	0.469
Dental insurance offered (binary)	0.436	0.496
Life insurance offered (binary)	0.571	0.533
Short-term disability offered (binary)	0.378	0.485
Long Term disability offered (binary)	0.329	0.470
Family leave offered (binary)	0.111	0.314
Fixed paid sick time (binary)	0.424	0.494
Consolidated sick plan PTO (binary)	0.163	0.369
Main employee occupations (sorted by weighted frequency)		
Office and administrative	0.166	0.372
Sales and related	0.113	0.316
Food preparation and serving	0.104	0.305
Transportation and material	0.086	0.281
Production	0.086	0.28
Health practitioners and technicians	0.061	0.240
Installation, maintenance, and repair	0.045	0.207
Management	0.042	0.200
Main employer industries (sorted by weighted frequency)		
Healthcare and social assistance	0.158	0.365
Retail trade	0.139	0.346
Manufacturing	0.120	0.325
Accommodation and food services	0.113	0.317
Admin, support and waste mgmt., and remed. services	0.072	0.258
Professional, scientific, and technical services	0.068	0.252
Finance and insurance	0.049	0.2180
Construction	0.049	0.2160
Wholesale trade	0.048	0.2140
Transportation and warehousing	0.040	0.1970
Employer size	612	2,127
Observations	399,586	

Source: National Compensation Survey (NCS) 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Yearly data at the employer-job level. Weights are provided by the BLS. Minimum and maximum values not available due to data confidentiality reasons.

Table 2: Effect of Mandates on Coverage, Utilization and Labor Costs

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean: (in treated localities)	0.659	17.8	0.541	567.6	0.326
Panel A					
Sick leave mandate	0.128***	1.983***	0.442**	51.566***	0.031***
($D_c \times T_t$)	(0.035)	(0.610)	(0.199)	(13.564)	(0.007)
Year FE	X	X	X	X	X
Employer FE	X	X	X	X	X
Panel B					
Sick leave mandate	0.129***	2.027***	0.441**	52.941***	0.032***
($D_c \times T_t$)	(0.034)	(0.587)	(0.199)	(13.189)	(0.007)
Year FE	X	X	X	X	X
Employer FE	X	X	X	X	X
Employee controls	X	X	X	X	X
Panel C					
Sick leave mandate	0.130***	2.060***	0.462*	54.211***	0.033***
($D_c \times T_t$)	(0.041)	(0.704)	(0.243)	(15.740)	(0.009)
Year FE	X	X	X	X	X
Employer-job FE	X	X	X	X	X
Panel D					
Sick leave mandate	0.128***	1.816**	0.479**	45.813***	0.027***
($D_c \times T_t$)	(0.038)	(0.701)	(0.193)	(16.288)	(0.008)
Year FE	X	X	X	X	X
Employer-job FE	X	X	X	X	X
State time trend	X	X	X	X	X

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. FE=fixed-effects. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Employee controls: union and part-time. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. Employers below the employer size cutoff are coded as zero. See Table B4 for results after dropping these observations.

Table 3: Effect Heterogeneity of Mandates: Coverage, Utilization and Labor Costs

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean: *(in treated localities)*	0.659	17.8	0.541	567.6	0.326
Panel A: Full-time vs. part-time					
Sick leave mandate	0.258***	1.656***	0.364**	18.579**	0.019***
($D_c \times T_t$)	(0.062)	(0.532)	(0.154)	(8.064)	(0.006)
Sick leave mandate	-0.182***	0.223	0.160	38.072***	0.011**
$\times$full-time	(0.032)	(0.262)	(0.184)	(12.228)	(0.005)
Panel B: Union vs. non-union					
Sick leave mandate	0.145***	1.950**	0.499**	42.864**	0.024**
($D_c \times T_t$)	(0.044)	(0.798)	(0.197)	(18.537)	(0.010)
Sick leave mandate	-0.168***	-1.310	-0.198***	28.874	0.027
$\times$union	(0.044)	(0.895)	(0.064)	(24.942)	(0.018)
Panel C: Large employers (>500 employees)					
Sick leave mandate	0.151***	1.828**	0.648***	35.211**	0.020**
($D_c \times T_t$)	(0.038)	(0.706)	(0.222)	(15.630)	(0.009)
Sick leave mandate	-0.120***	-0.059	-0.865***	54.078***	0.036***
$\times$large employers	(0.018)	(0.307)	(0.267)	(15.694)	(0.007)
Panel D: Small employers (<50 employees)					
Sick leave mandate	0.071**	1.640**	0.016	47.901**	0.024***
($D_c \times T_t$)	(0.028)	(0.749)	(0.110)	(19.683)	(0.008)
Sick leave mandate	0.153***	0.464**	1.243***	-5.813	0.006***
$\times$small employers	(0.022)	(0.229)	(0.373)	(8.830)	(0.002)

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Each column in each panel stands for one model similar to Equation (1), but augmented with triple interaction terms and all two-way interactions, see main text for details. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. All models in all panels control for year fixed-effects (FE), employer-job FE, and state-specific linear time trends (for estimations without trends see Table B5 in the Appendix). Controls for all other two-way interaction terms are included in all models but not shown (available upon request).

Table 4: Effect Heterogeneity of Mandates: Industries and Occupations

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean: *(in treated localities)*	0.659	17.8	0.541	567.6	0.326
Panel A: Industries					
Panel A1: Construction					
Sick leave mandate	0.119***	1.790**	0.445**	46.767***	0.028***
$(D_c \times T_t)$	(0.036)	(0.693)	(0.189)	(16.495)	(0.009)
Sick leave mandate	0.202***	0.589***	0.764***	-22.164***	-0.023***
×construction	(0.038)	(0.200)	(0.128)	(3.725)	(0.003)
Panel A2: Retail trade					
Sick leave mandate	0.121***	1.857**	0.561**	50.767***	0.029***
$(D_c \times T_t)$	(0.040)	(0.729)	(0.216)	(17.265)	(0.009)
Sick leave mandate	0.049***	-0.312	-0.605***	-36.583***	-0.017***
×retail trade	(0.011)	(0.234)	(0.204)	(8.792)	(0.003)
Panel A3: Admin and support and waste man. and remed. services					
Sick leave mandate	0.121***	1.864**	0.450**	49.063***	0.029***
$(D_c \times T_t)$	(0.039)	(0.738)	(0.219)	(17.556)	(0.009)
Sick leave mandate	0.070***	-0.501	0.307	-33.846***	-0.025***
×admin services	(0.021)	(0.399)	(0.538)	(12.538)	(0.007)
Panel A4: Accommodation and food services					
Sick leave mandate	0.104***	1.676**	0.131	48.240***	0.028***
$(D_c \times T_t)$	(0.037)	(0.673)	(0.096)	(17.382)	(0.009)
Sick leave mandate	0.184***	1.068***	2.679***	-19.134***	-0.011***
×accommodation	(0.033)	(0.182)	(0.758)	(6.301)	(0.003)
Panel B: Occupations					
Panel B1: Food preparation and serving					
Sick leave mandate	0.105***	1.685**	0.129	48.810***	0.028***
$(D_c \times T_t)$	(0.037)	(0.651)	(0.095)	(17.341)	(0.009)
Sick leave mandate	0.195***	1.139***	3.034***	-26.013***	-0.015***
×food	(0.035)	(0.288)	(0.820)	(5.823)	(0.003)
Panel B2: Sales and related					
Sick leave mandate	0.122***	1.920**	0.548**	50.915***	0.029***
$(D_c \times T_t)$	(0.039)	(0.755)	(0.215)	(17.884)	(0.009)
Sick leave mandate	0.052**	-0.942*	-0.630***	-46.357***	-0.024***
×sales	(0.025)	(0.503)	(0.204)	(14.033)	(0.007)
Panel B3: Office and administrative					
Sick leave mandate	0.140***	1.998**	0.550**	50.875***	0.030***
$(D_c \times T_t)$	(0.041)	(0.766)	(0.213)	(18.082)	(0.009)
Sick leave mandate	-0.075***	-1.145***	-0.447***	-32.035***	-0.019***
×office	(0.014)	(0.390)	(0.116)	(10.853)	(0.006)
Panel B4: Transportation and material					
Sick leave mandate	0.128***	1.776**	0.495**	44.618**	0.025***
$(D_c \times T_t)$	(0.037)	(0.686)	(0.201)	(17.095)	(0.009)
Sick leave mandate	-0.002	0.417*	-0.175*	12.589	0.021**
×transportation	(0.018)	(0.235)	(0.089)	(10.860)	(0.008)

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Each column in each panel stands for one model similar to Equation (1), but augmented with triple interaction terms and all two-way interactions, see main text for details. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. All models in all panels control for year fixed-effects (FE), employer-job FE, and state-specific linear time trends (for estimations without trends see Table B6 in the Appendix). Controls for all other two-way interaction terms are included in all models but not shown (available upon request).

Table 5: Decomposition of Treatment Effects

Outcome	**Weight**	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Timing_groups	0.020	0.119	0.926	0.318	52.250	0.024
Always_vs_timing	0.005	0.045	-1.323	0.908	-39.417	-0.022
Never_vs_timing	0.969	0.093	0.899	0.323	41.436	0.022
Always_vs_never	0.000	-2.618	-141.792	16.436	-8795.130	-5.114
Within	0.006	0.966	34.358	2.741	1216.231	0.625
Sick leave mandate		0.099***	1.089**	0.342***	48.042**	0.026**
($D_c \times T_t$)		(0.013)	(0.440)	(0.106)	(19.485)	(0.0101)

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights and estimated with employee controls (unionized employee and part-time employment). Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. Employers below the employer size cutoff are coded as zero. See Table B4 for results after dropping these observations.

Table 6: Effect of Sick Leave Mandates on Non-Mandated Benefits

	Insurance plans				Disability		Family	Paid sick leave	
	health	presc. drug	dental	life	short-term	long-term	leave	fixed	consolidated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pretreatment mean: *(in treated localities)*	0.698	0.685	0.515	0.531	0.264	0.311	0.119	0.474	0.135
Panel A									
Sick leave mandate	-0.009**	-0.004	0.003	-0.006	0.002	0.003	0.002	0.142***	-0.017***
$(D_c \times T_t)$	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.002)	(0.034)	(0.006)
Year FE	X	X	X	X	X	X	X	X	X
Employer FE	X	X	X	X	X	X	X	X	X
Panel B									
Sick leave mandate	-0.008*	-0.003	0.003	-0.005	0.002	0.004	0.002	0.142***	-0.017***
$(D_c \times T_t)$	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.004)	(0.002)	(0.034)	(0.006)
Year FE	X	X	X	X	X	X	X	X	X
Employer FE	X	X	X	X	X	X	X	X	X
Employee controls	X	X	X	X	X	X	X	X	X
Panel C									
Sick leave mandate	-0.006	-0.003	0.004	-0.004	0.002	0.005	0.002	0.142***	-0.018**
$(D_c \times T_t)$	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)	(0.002)	(0.041)	(0.007)
Year FE	X	X	X	X	X	X	X	X	X
Employer-job FE	X	X	X	X	X	X	X	X	X
Panel D									
Sick leave mandate	-0.012*	-0.009	-0.005	-0.002	0.001	0.004	0.002	0.131***	-0.007
$(D_c \times T_t)$	(0.006)	(0.007)	(0.007)	(0.005)	(0.004)	(0.005)	(0.002)	(0.040)	(0.008)
Year FE	X	X	X	X	X	X	X	X	X
Employer-job FE	X	X	X	X	X	X	X	X	X
State-spec. lin. time tr.	X	X	X	X	X	X	X	X	X

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. FE=fixed-effects. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Employee controls: unionized employee and part-time employment. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 observations, except for models (8) and (9) where we observe sick leave plans for 392,225 job year pairs. For an event study on health insurance see Figure B3.

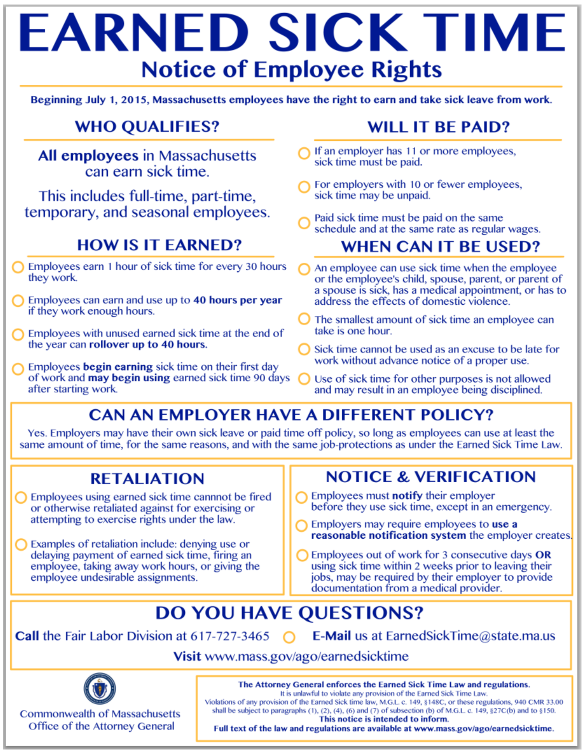
Table 7: Effect of Sick Leave Mandates on Hours Worked vs. on Paid Leave

	Annual hours			Total annual hours			Costs per hour		
	vacation (1)	holiday (2)	overtime (3)	worked (4)	paid leave (5)	paid (6)	wage (7)	health ins. (8)	non-production (9)
Pretreatment mean: (in treated localities)	69.92	46	48.79	1674.2	140	1814.3	24.67	0.97	3.591
Panel A									
Sick leave mandate	-0.253	-0.818***	0.776	-1.473	0.738	-0.734	0.334**	-0.036	-0.030*
($D_c \times T_t$)	(0.431)	(0.234)	(0.968)	(1.310)	(0.586)	(1.514)	(0.163)	(0.033)	(0.017)
Year FE	X	X	X	X	X	X	X	X	
Employer FE	X	X	X	X	X	X	X	X	
Panel B									
Sick leave mandate	-0.05	-0.724***	0.71	1.026	1.101**	2.127	0.229***	-0.034	-0.029
($D_c \times T_t$)	(0.376)	(0.267)	(1.108)	(1.557)	(0.436)	(1.293)	(0.044)	(0.033)	(0.018)
Year FE	X	X	X	X	X	X	X	X	
Employer FE	X	X	X	X	X	X	X	X	
Employee controls	X	X	X	X	X	X	X	X	
Panel C									
Sick leave mandate	0.083	-0.699**	0.881	0.983	1.266**	2.249	0.191***	-0.029	-0.024
($D_c \times T_t$)	(0.446)	(0.311)	(1.086)	(1.650)	(0.549)	(1.363)	(0.039)	(0.041)	(0.021)
Year FE	X	X	X	X	X	X	X	X	
Employer-job FE	X	X	X	X	X	X	X	X	
Panel D									
Sick leave mandate	0.503	-0.652*	1.31	1.462	1.373***	2.825**	0.203***	0.047	-0.035
($D_c \times T_t$)	(0.466)	(0.388)	(0.788)	(1.569)	(0.467)	(1.386)	(0.046)	(0.076)	(0.023)
Year FE	X	X	X	X	X	X	X	X	
Employer-job FE	X	X	X	X	X	X	X	X	
State-spec. lin. time tr.	X	X	X	X	X	X	X	X	

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. FE=fixed-effects. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Employee controls: unionized employee and part-time employment. The wage regression (7) includes the local minimum wage as additional control. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 observations.

Appendix

Figure A1: Examples of Legally Required Employee Right Notifications



Left figure shows an earned sick time poster from Massachusetts (Commonwealth of Massachusetts, 2019). Right figure shows a general workplace poster that is compliant with notification requirements in Arizona (Industrial Commission of Arizona, 2019). The Arizona poster includes all labor laws that employers are required to post at the workplace in Arizona.

Table A1: Overview of Employer Sick Pay Mandates in the United States (I)

Region (1)	County (2)	Law Passed (3)	Law Effective (4)	Content (5)
San Francisco, CA	SF	Nov 7, 2006	Feb 5, 2007	all employees including part-time and temporary; 1 hour of paid sick leave for every 30 hours worked; up to 5 to 9 days depending on employer size; for own sickness or family member; 90 days accrual period
Washington D.C.	D.C.	May 13, 2008	Nov 13, 2008	'qualified employees'; 1 hour of paid sick leave for every 43 hours, 90 days accrual period; up to 3 to 9 days depend. on employer size; own sickness or family; no health care or restaurant employees
		Dec 18, 2013	Feb 22, 2014 (retrosp. in Sep 2014)	extension to 20,000 temporary employees and tipped employees
Connecticut		July 1, 2011	Jan 1, 2012	full-time service sector employees at employers with >49 employees (20% of workforce); 1 hour for every 40 h up to 5 days; own sickness or family member, 680 hours accrual period (4 months)
Seattle, WA	King	Sep 12, 2011	Sep 1, 2012	all employees at employers with >4 full-time employees; 1 hour for every 30 or 40 hours worked; up to 5 to 13 days depending on employer size, for own sickness or family member; 180 days accrual period
New York, NY	Bronx, Kings, New York, Queens, Richmond	June 26, 2013 Jan 17, 2014 extended	April 1, 2014	employees w >80 hours p.a at employers >4 employees or 1 domestic employee; 1 hour for every 30 hours; up to 40 hours; own sickness or family member; 120 days accrual period
Portland, OR	Multnomah	March 13, 2013	Jan 1 2014	employees w >250 hours p.a. at emploeyrs >5 employees; 1 hour for every 30 hours; up to 40 hours; own sickness or family member
Jersey City, NJ	Hudson	Sep 26, 2013 Oct 28, 2015 extended	Jan 22, 2014	all employees at private employers with >9 employees; 1 hour for every 30 hours; up to 40 hours; own sickness or family; 90 days accrual period
Oakland, CA	Alameda	Nov 4, 2014	March 2, 2015	all employees at emmployers >9 employees; 1 hour for every 30 hours; 90 days accrual period; up to 40 to 72 hours depending on employer size; own sickness or family member
Newark, NJ	Essex	Jan 29, 2014	May 29, 2014	all employees in private companies; 1 hour for every 30 hours; 90 days accrual period; up to 24 to 40 hours depending on employer size; own sickness or family
Philadelphia, PA	Philadelphia	Feb 12, 2015	May 13, 2015	all employees at employers with >9 employees; 1 hour for every 40 hours; up to 40 hours; own sickness or family member; 90 days accrual period
California		September 19, 2014	July 1, 2015	all employees; 1 hour of paid sick leave for every 30 hours; minimum 24 hours; own sickness or family member; 90 days accrual period
Massachusetts		Nov 4, 2014	July 1, 2015	all employees at employers with >10 employees; 1 hour for every 40 hours; up to 40 hours; own sickness or family member; 90 days accrual period
Oregon		June 22, 2015	Jan 1, 2016	all employees at employers with >9 employees; 1 hour every 30 hours; 90 days accrual period; up to 40 hours; own sickness or family member

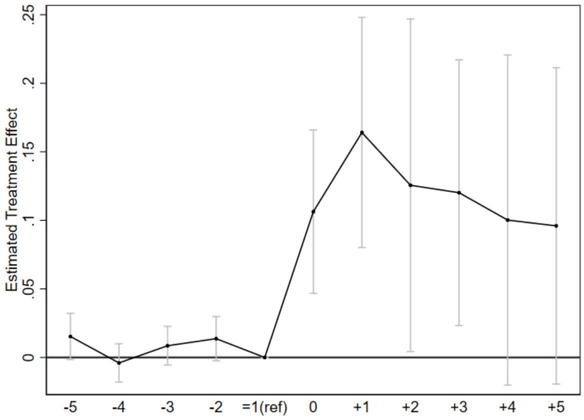
Source: several sources, authors' own collection and illustration.

Overview of Employer Sick Pay Mandates in the United States of America (II)

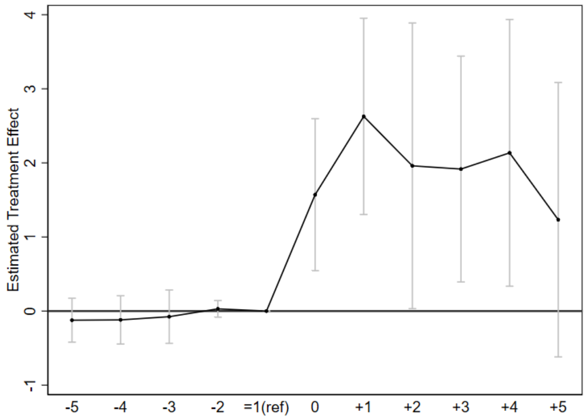
Region (1)	County (2)	Law Passed (3)	Law Effective (4)	Content (5)
Montgomery County		July 2, 2015	Oct 1, 2016	all employees except independent contractors, those without regular schedules and agency employe 1 hour every 30 hours; up to 56 hours p.a. at employers with >4 employees, up to 32 paid and 24 un at employers with < 5 employees; own sickness or family member; 90 days accrual
Vermont		March 9, 2016	Jan 1, 2017	employees w/ 18 hours/week & >20 weeks/year at employers with > 5 employees; 1 hour every 52 in 2017, 40 hours thereafter; own sickness or family member; underage employees and employers in some state employees & per diem employees in health care or long-term care facility exempt
Arizona		November 8, 2016	July 1, 2017	all employees; 1 hour for every 30 hours; up to 40 hours at employers with >14 employees, up to 24 hours <15 employees; own sickness or family member; employers can impose 90 day accrual period for new employees
Cook County & Chicago, IL		June 2, 2016	July 1, 2017	all employees w/ 80 hours in 120 days, some local gov employees exempt; 1 hour for every 40 hours; carry over half of unused up to 20 hours (40 hours if FMLA covered); can use up to 40 hours/years; own sickness or family member; 180 day accrual period for new employees
Minneapolis, MN	Hennepin County	May 26, 2016	July 1, 2017	all employees w/ 80 hours at employers with > 5 employees (<6 employees & first year of business: unpaid), ind. contractors exempt; 1 hour for every 30 hours up to 48 hours a year; own sickness or family member; 90 day accrual for n
Saint Paul, MN	Ramsey County	Sep 7, 2016	July 1, 2017 (at employers with >23 employees) Jan 1, 2018 (at employers with <24 employees)	all employees w/ 80 hours (first 6 months of business: unpaid), ind. contractors exempt; 1 hour for every 30 hours up to 48 hours a year own sickness or family member; 90 day accrual for new employees
Washington		Nov 8, 2016	Jan 1, 2018	all employees except those who are exempt from minimum wage law; 1 hour for every 40 hours; no than 40 hours carry over; own sickness or family member; 90 day accrual for new employees
Tacoma, WA	Pierce County	Sep 26, 2017	Jan 1, 2018	all employees w/ 80 hours; ind. contractors, single person employers, and fed. gov. employees exempt; 1 hour for every 40 hours; employers can cap carry over at 40 hours own sickness or family member; 90 day accrual period for new employees
Austin, TX	Travis County, (+ Hays & Williamson)	Feb 16, 2018	Oct 1, 2018 (employers with >4 employees) Oct 1, 2020 (employers with <5 employees)	all private sector employees w/ 80 hours , ind. contractors and unpaid interns exempt; 1 hour for every 30 hours up to 64 hours a year for employers with > 15 emp employers with <5 employees); own sickness or family member; 60 day accrual period for new emp
Maryland		Jan 12, 2018 (override veto by Governor)	Feb 11, 2018	employees w/ 12 hours/week at employers with > 14 employees (<15 employees 40 hours unpaid), 1 hour for every 30 hours; employers can cap at 64 hours accrual and 40 hours carry over; own sickness or family member, also for parental leave; certain groups exempt (e.g. temp. agency em
New Jersey		May 2, 2018	Oct 28, 2018	all employees; 1 hour for every 30 hours up to 40 hours/year; per diem health care employees exemp own sickness or family member; 120 day accrual for new employees; preempts city laws
Michigan		Dec 13, 2018 (weakened in lame duck session)	March 28, 2019	employees w/ 25 hours/week employed for 25 weeks at employers with > 49 employees; 1 hour for certain railway and air carrier employees exempt; own sickness or family member; 90 day accrual fo

Source: several sources, own collection, own illustration.

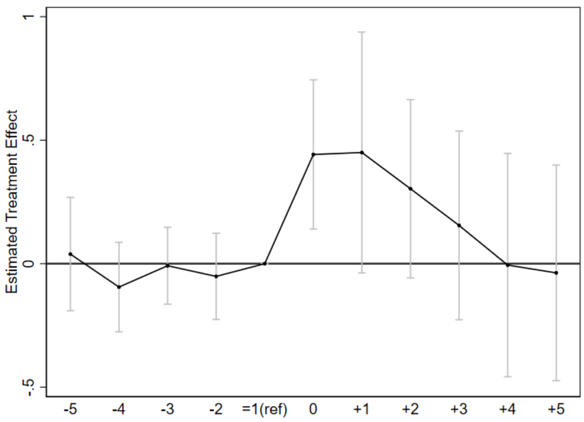
Figure B1: Event Studies from Difference-in-Differences Models (no state time trends)



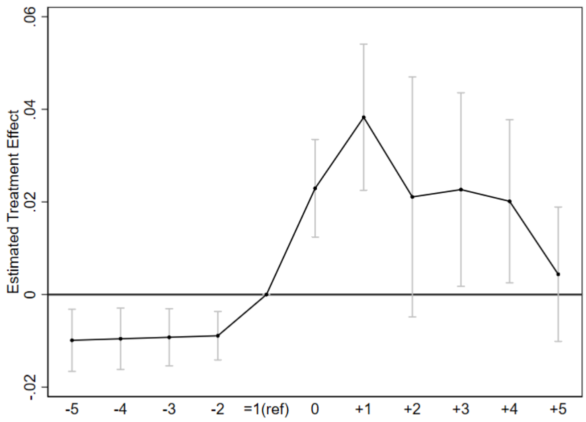
(a) Sick pay coverage



(b) Paid sick leave hours taken



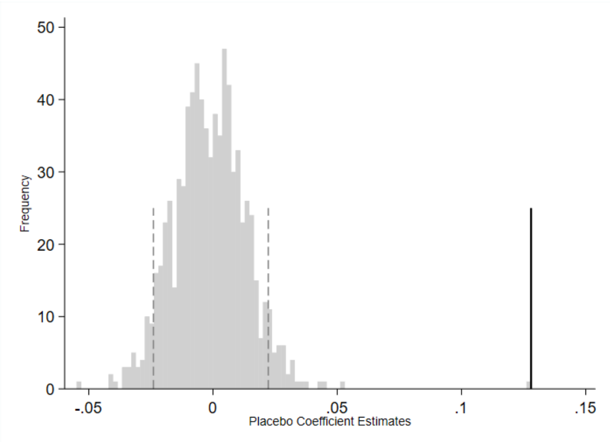
(c) Unpaid sick leave hours taken



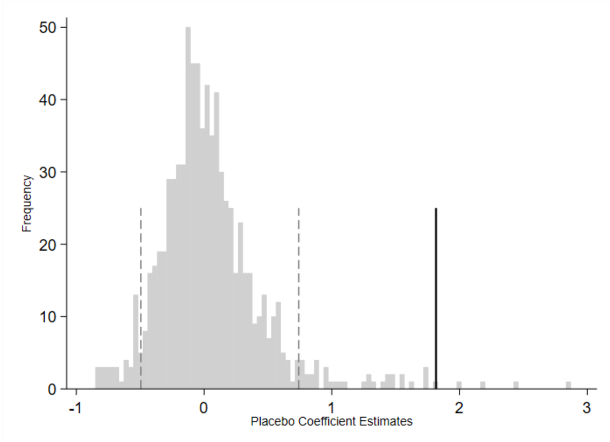
(d) Employer sick leave costs per hour worked

Notes: Source: National Compensation Survey (NCS) 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. The graphs show event studies based on DD models as in Equation (2). All models include employer-job fixed effects and time fixed effects. The errors terms are clustered at the state level and the gray bars depict 95% confidence intervals. The corresponding DD point estimates can be found in Panel D of Table 2. For more information about the sick pay reforms, see Table A1.

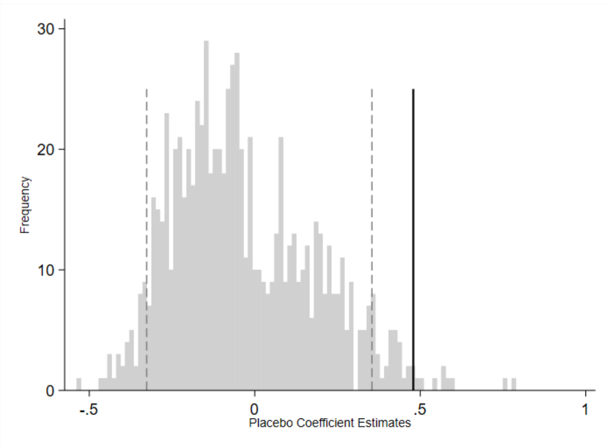
Figure B2: Placebo Regression Results (no state time trends)



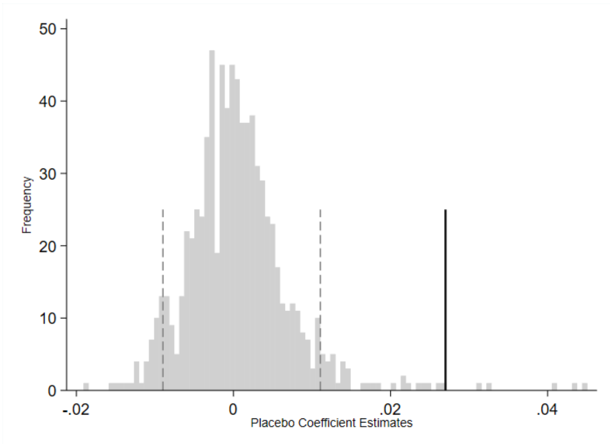
(a) Sick pay coverage (p=0.001)



(b) Paid sick leave hours taken (p=0.01)



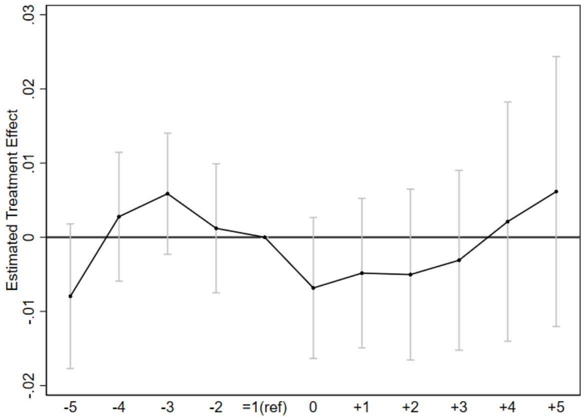
(c) Unpaid sick leave hours taken (p=0.05)



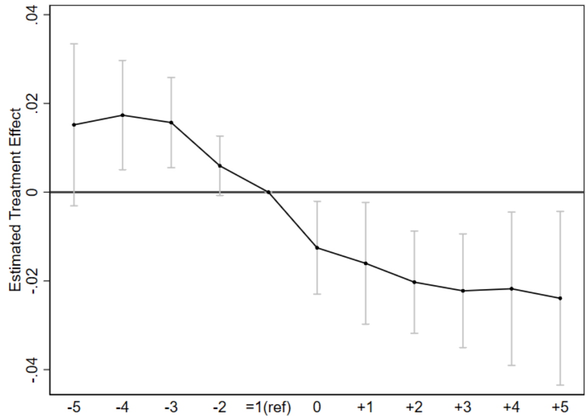
(d) Sick leave costs per hour worked (p=0.01)

Notes: Source: National Compensation Survey (NCS) 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. This figure plots the distribution of the estimated placebo regressions (n=200) that excluded treatment states and randomly assigned pseudo treatment states as compared to the true estimate. All models include employer-job fixed effects and time fixed effects. The vertical black line and corresponding bar denotes the coefficient estimates. The p-values are displayed next to the variable name. The corresponding DD point estimates can be found in Panel D of Table 2. For more information about the sick pay reforms, see Table A1.

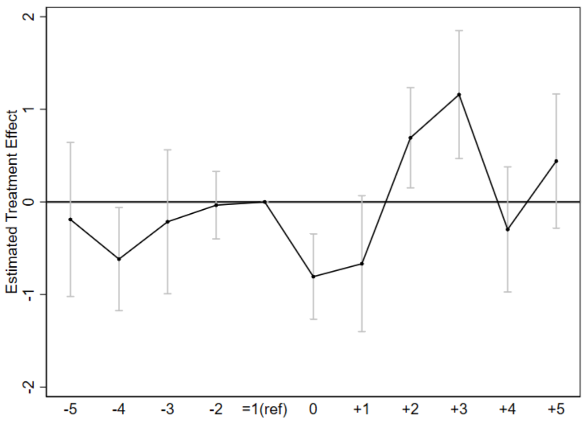
Figure B3: Event Study on Secondary Outcomes



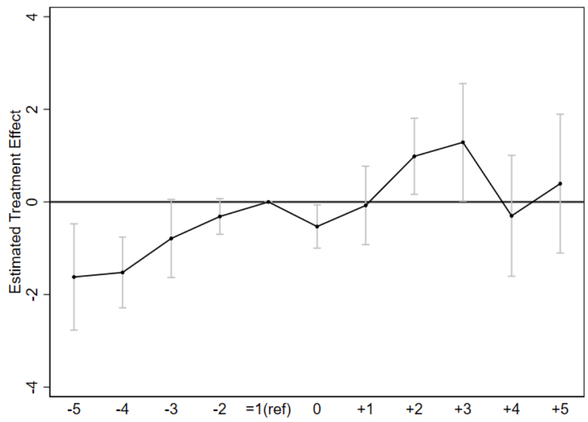
(a) Health insurance offered (no state trends)



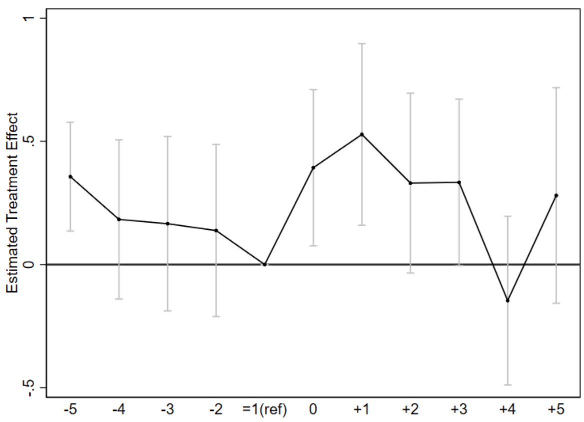
(b) Health insurance offered (including state trends)



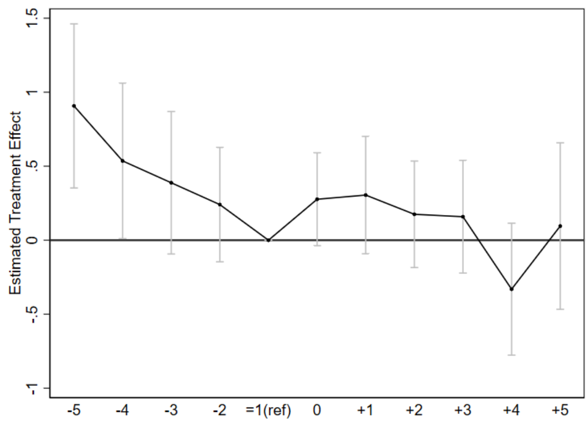
(c) Annual hours holiday (no state trends)



(d) Annual hours holiday (including state trends)



(e) Wages (no state trends)



(f) Wages (including state trends)

Notes: Source: National Compensation Survey (NCS) 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. The graphs show event studies based on DD models as in Equation (2). The corresponding point estimates are in column (1) of Table 6 (health insurance), in column (2) of Panels C and D of Table 7 (holiday hours), and in column (7) of Table 7 (wages). All models include employer-job fixed effects and time fixed effects. The error terms are clustered at the state level and the gray bars depict 95% confidence intervals. For more information about the sick pay reforms, see Table A1.

Table B1: Sick Leave Offered by Subgroup, 2009-2017 (weighted)

	N	Percent with sick leave offered
Inflation adjusted hourly wages		
Hourly wage $<$ 15\$	124,354	0.442
Hourly wage 15-25\$	125,710	0.73
Hourly wage 25-35\$	68,380	0.821
Hourly wage $\leq$ 35\$	81,142	0.885
Employer size		
$<$ 10employees	26,396	0.525
10-50 employees	57,333	0.52
50-100 employees	38,634	0.58
100-500 employees	114,480	0.696
$\leq$ 500 employees	162,743	0.825
Other characteristics		
Full-time employment	334,383	0.761
Part-time employment	65,203	0.268
Non-unionized	354,183	0.625
Unionized	45,403	0.714
Main employee occupations (sorted by weighted frequency)		
Office and administrative	85,343	0.753
Sales and related	36,629	0.56
Food preparation and serving	15,032	0.25
Transportation and material	26,091	0.562
Production	36,979	0.57
Health practitioners and technicians	31,167	0.816
Installation, maintenance, and repair	17,811	0.682
Management	23,356	0.919
Main employer industries (sorted by weighted frequency)		
Healthcare and social assistance	64,973	0.779
Retail trade	48,721	0.526
Manufacturing	64,595	0.659
Accommodation and food services	12,873	0.272
Admin and support and waste man. and remed. services	11,851	0.433
Professional, scientific, and technical services	11,779	0.846
Finance and insurance	59,183	0.933
Construction	17,978	0.423
Wholesale trade	16,718	0.784
Transportation and warehousing	12,494	0.72

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Yearly data at the employer-job level. Weights are provided by the BLS.

Table B2: County-Level Aggregation: Main Treatment Effects

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean:	0.659	17.8	0.541	567.6	0.326
Panel A					
Sick leave mandate	0.117***	1.385***	0.465***	58.396**	0.033***
$(D_s \times T_t)$	(0.028)	(0.478)	(0.143)	(25.291)	(0.011)
Year FE	X	X	X	X	X
County FE	X	X	X	X	X
Panel B					
Sick leave mandate	0.119***	1.477***	0.470***	61.853**	0.035***
$(D_s \times T_t)$	(0.026)	(0.428)	(0.149)	(24.049)	(0.011)
Year FE	X	X	X	X	X
County FE	X	X	X	X	X
Job controls	X	X	X	X	X
Panel C					
Sick leave mandate	0.149***	1.212***	0.255**	40.664***	0.014
$(D_s \times T_t)$	(0.021)	(0.362)	(0.120)	(14.500)	(0.010)
Year FE	X	X	X	X	X
County FE	X	X	X	X	X
State Time Trends	X	X	X	X	X

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Yearly data at the county level. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Job controls: union and part-time. Standard errors clustered at the state level and reported in parentheses. All models have 8,100 county-year observations.

Table B3: State-Level Aggregation: Main Treatment Effects

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean:	0.659	17.8	0.541	567.6	0.326
Panel A					
Sick leave mandate	0.107***	1.040**	0.369***	46.082**	0.024**
($D_s \times T_t$)	(0.023)	(0.394)	(0.119)	(21.549)	(0.010)
Year FE	X	X	X	X	X
State FE	X	X	X	X	X
Panel B					
Sick leave mandate	0.110***	1.125**	0.393***	49.123**	0.025**
($D_s \times T_t$)	(0.020)	(0.440)	(0.128)	(20.303)	(0.010)
Year FE	X	X	X	X	X
State FE	X	X	X	X	X
Job controls	X	X	X	X	X
Panel C					
Sick leave mandate	0.127***	0.532	0.173	33.808***	0.009
($D_s \times T_t$)	(0.027)	(0.444)	(0.130)	(12.228)	(0.009)
Year FE	X	X	X	X	X
State FE	X	X	X	X	X
State Time Trends	X	X	X	X	X

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Yearly data at the state level. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Job controls: union and part-time. Standard errors clustered at the state level and reported in parentheses. All models have 451 state-year observations.

Table B4: Dropping Employers below Employee Size Mandate Threshold

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean: 0.657	17.69	0.544	564.5	0.324	
Panel A					
Sick leave mandate	0.137***	2.146***	0.436**	56.216***	0.034***
($D_s \times T_t$)	(0.032)	(0.557)	(0.216)	(11.516)	(0.006)
Year FE	X	X	X	X	X
Employer FE	X	X	X	X	X
Panel B					
Sick leave mandate	0.138***	2.190***	0.435**	57.621***	0.035***
($D_s \times T_t$)	(0.031)	(0.531)	(0.216)	(11.064)	(0.006)
Year FE	X	X	X	X	X
Employer FE	X	X	X	X	X
Employee controls	X	X	X	X	X
Panel C					
Sick leave mandate	0.139***	2.228***	0.458*	59.032***	0.035***
($D_s \times T_t$)	(0.037)	(0.632)	(0.263)	(13.101)	(0.007)
Year FE	X	X	X	X	X
Employer-job FE	X	X	X	X	X
Panel D					
Sick leave mandate	0.136***	1.968***	0.464**	49.862***	0.028***
($D_s \times T_t$)	(0.037)	(0.659)	(0.228)	(14.798)	(0.008)
Year FE	X	X	X	X	X
Employer-job FE	X	X	X	X	X
State Time Trends	X	X	X	X	X

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Yearly data at the employer-job level. Each column in each panel stands for one DD model as in Equation (1). ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Employee controls: unionized employee and part-time employment. Standard errors clustered at the state level and reported in parentheses. All models have 393,609 employer-job observations.

Table B5: Effect Heterogeneity: Coverage, Utilization and Labor Costs (no state time trends)

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean:	0.659	17.8	0.541	567.6	0.326
Panel A: Full-time vs. part-time					
Sick leave mandate	0.259***	1.893***	0.341*	26.782***	0.025***
($D_s \times T_t$)	(0.066)	(0.536)	(0.194)	(7.608)	(0.006)
Sick leave mandate	-0.180***	0.233	0.168	38.262***	0.011**
$\times$full-time	(0.033)	(0.265)	(0.181)	(12.374)	(0.005)
Panel B: Union vs. non-union					
Sick leave mandate	0.147***	2.189***	0.480*	51.156***	0.030***
($D_s \times T_t$)	(0.047)	(0.805)	(0.247)	(18.000)	(0.010)
Sick leave mandate	-0.165***	-1.258	-0.177**	29.770	0.027
$\times$union	(0.046)	(0.921)	(0.080)	(25.252)	(0.018)
Panel C: Large employers (>500 employees)					
Sick leave mandate	0.154***	2.089***	0.634**	44.301***	0.026***
($D_s \times T_t$)	(0.040)	(0.696)	(0.269)	(14.572)	(0.009)
Sick leave mandate	-0.124***	-0.154	-0.884***	50.870***	0.033***
$\times$large employers	(0.017)	(0.293)	(0.256)	(17.124)	(0.008)
Panel D: Small employers (<50 employees)					
Sick leave mandate	0.071**	1.871**	-0.004	56.023***	0.030***
($D_s \times T_t$)	(0.031)	(0.763)	(0.126)	(19.424)	(0.008)
Sick leave mandate	0.157***	0.503*	1.249***	-4.966	0.007**
$\times$small employers	(0.022)	(0.286)	(0.372)	(9.917)	(0.003)

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Each column in each panel stands for one model similar to Equation (1), but augmented with triple interaction terms and all two-way interactions, see main text for details. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. All models in all panels control for year FE and employer-job FE. Controls for all other two-way interaction terms are included in all models but not shown (available upon request).

Table B6: Effect Heterogeneity: Industries and Occupations (no state time trends)

Outcome	**Sick leave offered (1)**	**Paid sick hours taken (2)**	**Unpaid sick hours taken (3)**	**Sick leave costs total (4)**	**Sick leave costs per hour (5)**
Pretreatment mean: (in treated localities)	0.659	17.8	0.541	567.6	0.326
Panel A: Industries					
Panel A1: Construction					
Sick leave mandate	0.121***	2.030***	0.427*	55.110***	0.034***
($D_c \times T_t$)	(0.039)	(0.696)	(0.238)	(15.970)	(0.009)
Sick leave mandate	0.207***	0.662***	0.789***	-20.666***	-0.022***
$\times$construction	(0.037)	(0.211)	(0.126)	(5.113)	(0.004)
Panel A2: Retail trade					
Sick leave mandate	0.123***	2.103***	0.545**	59.184***	0.035***
($D_s \times T_t$)	(0.042)	(0.732)	(0.265)	(16.763)	(0.009)
Sick leave mandate	0.049***	-0.319	-0.613***	-36.655***	-0.017***
$\times$retail trade	(0.010)	(0.226)	(0.198)	(8.755)	(0.003)
Panel A3: Admin and support and waste man. and remed. services					
Sick leave mandate	0.123***	2.110***	0.432	57.533***	0.035***
($D_c \times T_t$)	(0.042)	(0.737)	(0.270)	(16.906)	(0.009)
Sick leave mandate	0.069***	-0.530	0.313	-34.673***	-0.026***
$\times$admin services	(0.022)	(0.399)	(0.542)	(11.971)	(0.007)
Panel A4: Accommodation and food services					
Sick leave mandate	0.105**	1.911***	0.111	56.470***	0.034***
($D_s \times T_t$)	(0.040)	(0.685)	(0.127)	(17.054)	(0.009)
Sick leave mandate	0.186***	1.138***	2.682***	-17.395**	-0.010**
$\times$accommodation	(0.035)	(0.211)	(0.757)	(8.384)	(0.004)
Panel B: Occupations					
Panel B1: Food preparation and serving					
Sick leave mandate	0.107**	1.921***	0.107	57.085***	0.034***
($D_s \times T_t$)	(0.040)	(0.660)	(0.126)	(16.944)	(0.009)
Sick leave mandate	0.199***	1.195***	3.049***	-24.734***	-0.014***
$\times$food	(0.037)	(0.267)	(0.810)	(7.330)	(0.004)
Panel B2: Sales and related					
Sick leave mandate	0.124***	2.165***	0.531*	59.355***	0.035***
($D_s \times T_t$)	(0.042)	(0.755)	(0.265)	(17.283)	(0.009)
Sick leave mandate	0.053**	-0.958*	-0.627***	-46.690***	-0.024***
$\times$sales	(0.026)	(0.495)	(0.211)	(13.656)	(0.007)
Panel B3: Office and administrative					
Sick leave mandate	0.142***	2.242***	0.530*	59.358***	0.036***
($D_s \times T_t$)	(0.043)	(0.767)	(0.264)	(17.468)	(0.009)
Sick leave mandate	-0.075***	-1.151***	-0.433***	-32.440***	-0.020***
$\times$office	(0.014)	(0.387)	(0.129)	(10.529)	(0.005)
Panel B4: Transportation and material					
Sick leave mandate	0.130***	2.016***	0.478*	52.907***	0.031***
($D_s \times T_t$)	(0.040)	(0.692)	(0.250)	(16.595)	(0.009)
Sick leave mandate	-0.001	0.468*	-0.172*	13.819	0.022***
$\times$transportation	(0.019)	(0.244)	(0.088)	(11.317)	(0.008)

Source: NCS 2009-2017 (Bureau of Labor Statistics, 2020b), authors' own calculation and illustration. Each column in each panel stands for one model similar to Equation (1), but augmented with triple interaction terms and all two-way interactions, see main text for details. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level. All models are weighted using NCS weights. Standard errors clustered at the state level and reported in parentheses. All models have 399,586 employer-job observations. All models in all panels control for year FE and employer-job FE. Controls for all other two-way interaction terms are included in all models but not shown (available upon request).