The Impact of Mandated Paid Sick Leave Laws on The Long-Term Care Industry

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Abstract

This paper examines the effect of paid sick leave mandates on nursing home outcomes, with a focus on low paid nursing staff. I use the synthetic control group method and traditional difference-in-differences models along with Nursing Home Compare data and Vital Statistics microdata to estimate the causal effect of paid sick leave mandates on nursing home outcomes. I find significant increases in part-time nursing assistant staffing and improvements in resident health and safety. Nursing homes in areas with sick pay mandates also show reductions in the elderly mortality rate. Nursing assistant hours per resident day increase by 2.3 percent driven by a 12 percent increase in the hours for part time workers, and there are no significant reductions in hours of full time nursing assistants. I find improvements along multiple measures of patient health and safety. My calculations show that sick pay mandates helped prevent at least 4000 nursing home deaths among the elderly.

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1 Introduction

In 2019, less than a third of workers in the bottom 10 percent of the income distribution had access to paid sick leave (PSL), compared to 90 percent of workers in the top quarter of the income distribution (BLS, 2020). Nursing assistant is one of the lowest paid occupations in the United States and in 2019 had a median wage of about 14 dollars with almost 34 percent exposed to increases in the minimum wage from 2014-2018 (Ruffini, 2020). Information regarding paid sick leave availability among nursing assistants is varied[1]. However, most reports point to the fact that there are many nursing assistant jobs which do not have paid sick leave (Dill et al., 2013). Data from the National Health Interview Survey covering 2014-2018 show that only 55 percent of nursing assistants receive paid sick leave. As higher-wage earners are more likely to be covered by an employer's PSL policy when not mandated by law, universal requirements can help level the playing field.

The United States along with Japan are the only two industrialized nations without universal access to PSL. The recent Family First Coronavirus Response Act[2], provides up to two weeks of paid sick time at 100 percent of the person's salary, however the legislation is temporary and expired at the end of 2020. Sick workers are less productive than those at full health (Goetzel et al., 2004) and coming to work sick can be especially risky in a fragile setting like the long-term care industry. This makes nursing assistants and their patients especially vulnerable. When facilities do not offer separate paid time off for sickness, those with access to paid vacation or unallocated paid time off may be reluctant to use it when sick, instead preferring to save it for other uses. The majority of nursing assistants are women, minorities, have less than a college education, and come from low income households. When faced with a choice of whether to stay at home or come to work when sick, a difficult financial position may increase their likelihood of choosing the unhealthy and unproductive option of coming in to work.

This paper explores the effect of state mandated PSL laws on the long-term care industry,

[1] Analysis based on data from a 2004 survey Squillace et al. (2009) points to 70 percent of nursing assistant having access to paid leave. However, the survey does not separate between paid time off and paid sick leave.

[2] This act exempts health care workers, however, the HEROES Act, passed on May 15, removes this exemption.

with a special focus on nursing assistants and residents. I examine how these laws affect nursing assistant staffing, patient conditions, and elderly nursing home mortality rate. I calculate the age adjusted elderly mortality rate from Vital Statistics microdata and use objective measures of patient health and safety from the near universe of nursing homes in the United States. I estimate the effect of a PSL mandate on these outcomes by exploiting the temporal and spatial variation in the implementation of city and statewide PSL mandates. Some nursing assistants may already have PSL which, may improve nursing quality, but, state mandated PSL may lead nursing homes to increase the amount of sick time they offer to their staff. Conversely, PSL mandates may lead nursing homes to reduce staff, or even reduce the salaries paid, which may reduce quality of care. Nursing homes may also want to keep staff hours constant by increasing the number of part-time staff available to substitute for possible increases in leave taking by full time staff. Since the effects are theoretically ambiguous, the answer to how this policy will affect nursing home quality must be determined empirically.

To examine the effect of mandated PSL laws on quality of care in nursing homes, I use two well established empirical methods in the applied microeconomics literature. First, I use traditional difference-in-differences models to estimate the effect of PSL mandates on nursing assistant staffing and nursing home patient conditions. Second, I use the synthetic control group method (SCGM) to estimate the effect of PSL mandates on nursing home elderly mortality rate. The setting of this paper is well-suited for the application of the SCGM. First, I can match the elderly nursing home mortality rate of the treated units for a long pre-reform time period. Second, the regions are heterogeneous in terms of size, nursing home mortality rate and population density, and thus provide broad common support. As a result, the findings should have external validity for other U.S. areas with a similar nursing home structure and policy environment. The rich temporal and spatial variation in PSL mandates allows for comparison of patient well-being due to changes in non-wage labor costs, along with flexibly accounting for demographic and economic changes at a small geographic level. I leverage nursing home level information from the Centers for Medicare and Medicaid's (CMS) OSCAR (Online Survey Certification & Reporting System) and CASPER (Certification And Survey Provider Enhanced

Reports) data sets along with death counts from all county multiple cause of death microdata to look at a variety of measures widely considered to be indicators of facility quality and patient well-being.

I show that PSL mandates do not lead to a decrease in full time staffing hours and lead to increases in part-time nursing assistant hours. This is consistent with existing literature on the effects of PSL mandates on aggregated labor markets (Pichler and Ziebarth (2019); Stearns and White (2018)). Increased part time staff hours lead to an increase in average nursing assistant hours per resident. I find that nursing assistant's time spent with patients go up by 2.3 percent following the enactment of PSL mandates. Nursing homes in areas with PSL mandates show a 12 percent increase in part-time nursing assistant hours compared to those in areas without mandated PSL laws.

If PSL mandates reduce the likelihood of presenteeism, health care quality should improve. In order to explore this further, I look at the impact of PSL mandates on common health care quality measures for nursing homes. I find that PSL mandates improve patient health and reduce the severity of safety violations. Specifically, I show that PSL mandates reduce the share of residents with pressure ulcers and on anti-psychotic medications by 12 percent and 5 percent respectively. I also find that severe violations are reduced by 7.5 percent. I perform event study analyses and do not find strong evidence of preexisting trends in any outcome. Further, I observe persistent improvements in patient health and nursing home staffing after the mandate. I also provide evidence of how PSL mandates affect ederly nursing home mortality rate using the SCGM. My analysis shows the prereform outcome dynamics of the treated group to closely match that of the synthetic control group, thus providing support for valid counterfactuals. I find that PSL mandates lead to a 5.5 percent fall in the elderly nursing home mortality rate, translating to a reduction in 4479 deaths.

The nursing home industry serves almost 1.6 million elderly residents across the United States. In spite of the CMS introducing several regulations to ensure quality of care, there are still significant variations in the quality of care provided. It may be the case that lower quality nursing homes are the ones where the PSL mandates are binding and have the strongest effects. Exploring possibilities of heterogeneous outcomes, I find that most improvements in care quality are driven by outcomes from nursing homes with a high share of Medicaid patients. Enactment of PSL mandates also leads to nursing homes getting a change in patient composition along several margins, which includes healthier patients and a slight increase in private-paying patients. However, I find no significant reduction in the share of Medicaid or Medicare paying patients.

Contagious presenteeism behavior by aides and orderlies can be life-threatening for patients, but, can be potentially minimized by paid sick time. The findings from this study provide evidence as to how PSL mandates can impact the long-term care industry. More than half of individuals reaching age 65 will require long-term care at some point in their lives, much of which is provided in residential settings (Favreault and Dey, 2016). Making up more than 10 percent of the total expenditure in Medicare and Medicaid, the long-term care industry accounts for a substantial portion of the U.S. economy. As the elderly share of the U.S. population continues to grow, the effect of paid sick leave mandates on nursing home patient well-being is an increasingly important policy question.

1.1 Research on Sick Leave

State mandated PSL is a recent phenomenon in the United States. Literature on the effects of such mandates is new and growing. There does not exist any work examining the effect of such mandates on the nursing home industry. Nonetheless, there are multiple studies looking at how PSL mandates impact productivity, employment, and health outcomes of workers in general. This paper is the first to look at the effects of PSL mandates on the nursing home industry. It is an industry where a significant portion of workers are low paid, don't have access to PSL, and attending work ill can have large negative effects.

My paper contributes to multiple strands of literature in economics and public health. Existing literature finds mixed evidence of the effects of the mandates on employment. Connecticut was the first state to implement the policy in 2012, and, reports have found reductions in annual hours worked (Ahn and Yelowitz, 2016) along with increased unemployment and economically insignificant changes in labor force participation (Ahn and Yelowitz, 2015). However, more recent work looking at a longer timeline and multiple states have found no significant reductions in employment or wage growth (Pichler and Ziebarth, 2019).

This paper also contributes to a small but growing literature studying the effects of PSL mandates on worker productivity. A survey of New York City businesses found that the large majority of businesses observed no effect on productivity, with only 2 percent reporting that productivity had increased, and 4 percent reporting that productivity decreased (Appelbaum and Milkman, 2016) from PSL mandates. Additionally, a survey in Jersey City found more than a third of businesses noticing improvements in productivity (Lindemann and Britton, 2015). Worker satisfaction has also improved following enactments of PSL mandates. More than half of employees in San Francisco who previously had access to PSL reported improved employer support and an increase in the number of sick days provided (Drago et al., 2011). Productivity of workers also improves through improved health outcomes of workers. The lowest-income group of workers without paid sick time were at the highest risk of delaying and forgoing medical care for themselves and their family members (DeRigne et al., 2016). PSL mandates have also been shown to reduce aggregate illness related leave taking (Stearns and White, 2018). Thus, existing literature points to substantial public health externalities of PSL mandates through reduced spread of illness and disease to coworkers and customers.

1.2 Research on the Long-term care industry

My paper contributes to the public health literature focusing on the long-term care industry. Increased staffing through laws and business cycle changes have been shown to reduce violations and mortality (Chen and Grabowski (2015); Matsudaira (2014); Park and Stearns (2009); Antwi and Bowblis (2018); Stevens et al. (2015)). Reduced staffing through unionization does not harm patient outcomes, which shows that labor policies may influence worker productivity (Sojourner et al., 2015). I find that PSL mandates increase time spent by staff on patients, similar to results achieved from wage increases and increased staff attention (Grabowski et al., 2011). Changes in staff turnover driven by macroeconomic fluctuations have also been shown to reduce mortality and the number of violations (Antwi and Bowblis (2018); Stevens et al. (2015). Other state and city level policies like minimum wages have also been shown to improve (Ruffini, 2020) patient health and safety outcomes in nursing homes.

The remainder of this paper proceeds as follows. Section 2 describes the nursing home industry and paid sick leave laws. Section 3 outlines the data. Section 4 describes the empirical framework. Section 5 presents results, and Section 6 describes the robustness checks, and Section 7 concludes.

2 Institutional Details

2.1 Nursing homes

The United States has almost 16,000 nursing homes which provide round-the-clock care to their residents. The 1.4 million residents of nursing homes receive health, personal care, supportive and rehabilitative services. The vast majority of these residents are 65 years or older, with a significant number being 80 years or older. They receive routine assistance in a number of day-to-day activities ranging from eating, bathing, dressing, mobility, and toileting (Centers for Medicaid and Medicare Services, 2015). Due to the relatively inelastic demand for their service, most nursing homes have very high occupancy rates. These facilities are also extremely labor intensive and employ nearly 1.6 million workers, with around 40 percent being nursing assistants (Ruffini, 2020). Due to the considerable amount of time nursing assistants spend with elderly and fragile residents, their tasks can directly affect patient well-being. They provide basic patient care under the direction of nursing staff. Their primary duties are to feed, bathe, dress, groom, or move patients, and change linens (ONET, 2019).

Nursing homes have to fulfill several federal reporting and inspection requirements. The 1987 Nursing Home Reform Act (NHRA), requires annual independent health inspections; nursing credentialing, minimum RN staffing levels, and routine, comprehensive patient assessments (Castle and Ferguson (2010); Institute of Medicine (1986)). Fulfilling these requirements makes nursing homes eligible to receive Medicare and Medicaid reimbursement. The nursing home market has significant barriers to entry: certificate of need laws places limits on construction and the number of beds each facility can have in many states (NCSL (2019); Centers for Medicaid and Medicare Services (2015)). Only 26 percent of residents pay out of pocket for nursing home stays, with the rest coming from Medicare (12 percent) and Medicaid(62 percent) reimbursement. Medicaid reimbursement rates are 30 percent lower than Medicare's on average and are roughly half of out-of-pocket prices. These reimbursement rates are set by expected patient costs, with Medicaid rates depending on state payment structures and Medicare rates on service needs and local cost-of-living adjustments (Houser et al. (2018); Centers for Medicaid and Medicare Services (2019)). Residents paying out of pocket are in general, much more responsive to quality and prices than those covered by public insurance (Gertler, 1989).

2.2 Paid Sick Leave

The Family and Medical Leave Act of 1993 (FMLA), is the only existing federal law that provides sick leave. However, it is fairly restrictive compared to recent local mandates providing only unpaid leave to employees with at least 1250 hours worked annually at a business with greater than or equal to 50 employees (Tominey, 2016). The restrictive nature of this bill leaves out 49 million workers, almost 44 percent of all employees (Jorgensen and Appelbaum, 2014). Table 1 provides a summary of the mandates effective on or before 2018. The details of the bills differ by jurisdiction, but nearly all sick pay mandates are employer mandates.

The first PSL mandate requiring employers to provide paid sick days was implemented in San Francisco in 2007. Connecticut became the first state in the U.S. to enact PSL legislation in 2012. The Connecticut law mandated that firms with 50 or more employees offer paid sick time to service workers; the San Francisco policy included no such exemptions based on firm size or industry. I study PSL mandates from 9 states, and 10 localities for nursing home staffing and nursing home level patient conditions. I study PSL mandates from Connecticut, Massachusetts, California and New York City to study the effect of these mandates on elderly nursing home mortality. These states span several regions, from New England (Connecticut, Massachusetts, Vermont, Rhode Island), the West (California, Oregon, Washington, Arizona), and the Mid-Atlantic (Maryland, New Jersey)[3]. The localities with PSL mandates in my sample consist mostly of large cities and counties located in the above states, as well as New York City; Philadelphia, PA; Minneapolis and St. Paul, MN; Chicago and Cook County, IL. Twenty-two states have passed preemption laws preventing localities from requiring employers to provide PSL. These include four states that concurrently passed statewide laws that prohibit localities from establishing PSL requirements that differ from existing state standards.

Almost all states mandate a sick leave accrual rate between 1 and 1.3 hours per 40 hours. Some localities cap the amount of sick time that can be accrued, oftentimes tying the limit to the size of the employer. A preponderance of localities specify that paid sick time can be used for reasons related to domestic violence or sexual assault as well as to care for oneself or a family member. Virtually all of the local laws include exemptions, many of them related to the number of hours an employee works. For instance, the law in Cook County, IL, exempts employees who work less than 80 hours a year. There are also laws exempting health care workers, for instance Washington DC's 2009 law exempts health care workers and hence is not part of my sample. Long-term care workers in Vermont and New Jersey who work on a per diem basis are also exempt from the law.

3 Data

My primary sources of data are the online survey certification and reporting (OSCAR) and certification and survey provider enhanced reporting (CASPER) data from the CMS. Nursing facilities are required to report staffing numbers and patient characteristics to CMS in order to be eligible for Medicaid and Medicare reimbursement. During the analysis period, these data are based on staffing numbers for the two weeks before an unannounced health and safety inspection (Centers for Medicare and Medicaid, 2020). For 2000-2018, the OSCAR/CASPER data provide two measures of employment for nursing assistants: hours per resident per day, and the number of full-time equivalent (FTE) staff by part-time, full-time, and contractor status.

[3]The most recent state to enact a PSL mandate is Michigan, coming in to effect March 2019

Assuming full time staff work 35 hours a week, the number of FTE full-time staff is the total hours worked by full-time staff in the week, divided by 35. Full-time staff are defined as those working at least 35 hours a week, and part time are those working fewer than 35 hours a week. Staffing hours per resident day are provided by the Brown School of Public Health (2020), denoted as the number of FTE multiplied by 35 from the OSCAR/CASPER data, divided by the number of residents in the facility, and then processed to account for implausibly large year-to-year fluctuations in staffing levels.

As with staffing information, facilities are required to report information on patient conditions to CMS to be eligible for reimbursement. These assessments are conducted by facility staff and are subject to a CMS audit. My analyses focus on the fraction of residents with conditions that are most likely to be affected by the quality and quantity of nursing care: moderate-to-severe pressure ulcers; urinary tract infections (UTI); physical restraints; or psychotropic medication. I focus only on long-term stays (residents in a facility for at least 100 days), as these patients have the longest exposure to a facility's nursing staff.

State surveyors conduct unannounced health inspections every 9-15 months on nursing homes, and, interview staff, patients, and family members about the quality of care (Associates Inc and Abt Associates Inc. (2013); Centers for Medicaid and Medicare Services (2015)) . OSCAR/CASPER data has the type, number, severity, and scope of each violation a facility has received, as well as the date the inspection occurred. There are a number of violations closely associated with patient safety measures and measures of worker productivity like routinely assessing residents, communicating patient conditions to family members, changing bed linens, avoiding accident hazards, and providing sanitary food preparation.

Following Ruffini (2020), I use every violation a facility has received since 2000 and construct several measures of patient safety. I consider both the total number of violations and the number of severe violations that present immediate harm or danger to residents. I create two measures of violations following Ruffini (2020). The first considers all health violations. The second, considers Quality of Care(QOC) violations. The QOC measure includes violations in the assessment relating to quality of care, nursing, dietary, physician, rehabilitative services, dental, and pharmacy regulation categories. These violations are the subset of violations widely recognized in the public health literature to be most closely related to nursing responsibilities (Chen and Chen (2019), Harrington et al. (2000), Harrington et al. (2002), Antwi and Bowblis (2018)). Violations are not uncommon in nursing homes and almost all nursing homes have at least one recorded violation every year, with the average nursing home having 7 violations. Violations depending on the scope and severity can lead to substantial number of fines and penalties. Reduced violations may lead to significant cost savings for nursing homes.

Average patient age, and the share of female residents and other demographic variables used are available from the Minimum Data Set and provided through Brown School of Public Health (2020). All the main specifications also control for county-level demographic and economic controls that change over time. Total and elderly population figures are available through the National Institute of Health (2020). To account for local labor market conditions, I control for the overall county unemployment rate using data from Bureau of Labor Statistics (2020). Finally, to ensure my results are not driven by the overall state policy environment or other policy changes coincident with PSL mandates, I control for state EITC parameters, the share of the elderly population receiving Supplemental Security Income (SSI), a proxy for Medicaid-eligibility, and AFDC/TANF caseloads and benefit levels from the University of Kentucky (2020). The share of Medicaid claimants at the establishment level, as well as private ownership and chain status, are provided through Brown School of Public Health (2020). My sample has on average, slightly more than 15,000 facilities and around 3000 counties over a 19-year time span.

Finally, I calculate state-year and county-year mortality rates for elderly nursing home residents using death counts from Vital Statistics micro-record multiple cause of death files and county-by-age population counts from the National Institute of Health (2020). I follow the methodology first discussed in Stevens et al. (2015) that adjusts the outcome to create a measure of mortality rate that holds the age distribution constant over time. Nursing home deaths are identified as those occurring in nursing home/long term care centers. The age adjusted mortality rate measure at the county-level[4] is defined as follows:

$$m_{cy} = \Sigma_{a=65}^{85+} \frac{deaths_{cay}}{pop_{cay}} * \frac{pop_{a,2010}}{\Sigma_{k=65}^{85+} pop_{k,2010}} \tag{1}$$

Where $deaths_{cay}$ is the number of deaths in nursing home settings among individuals aged a in county c in year y from the Vital Statistics data, and pop_{cay} is the population size of individuals aged a in each county-year from the National Institute of Health (2020). $\frac{pop_{a,2010}}{\Sigma_{k=65}^{85+} pop_{k,2010}}$ is the national fraction of individuals age a in the elderly population in year 2010. For the mortality analysis I only consider areas with at least 3 post treatment periods in my analysis. Detailed information on areas which mandated paid sick leave laws on or before 2015 are provided in Table A4. I also restrict my main analysis to the 4 treatment regions of California, Connecticut, Massachusetts, and New York City. All 4 of these areas have much higher levels of nursing home beds than the remaining smaller areas. For example, Connecticut is the area with the smallest number of beds among my main treatment areas, but, it still has almost 4 times the number of beds as the next largest area Philadelphia. This distinction is important as small changes in the number of deaths in an already narrowly defined outcome variable can cause large relative changes in the outcome variable. In appendix Table A6 I provide results for additional counties.

Table 2 reports information on the control variables used in my analysis. I find large differences along a number of policy variables like minimum wage and state EITC. Facilities in treatment areas are also larger on average and face lower levels of competition. My treatment counties are on average more urban and have a younger population. These localities, predominantly located along the coasts, also largely vote democratic and have seen a large number of changes in labor laws and safety nets, which explains the higher minimum wages and level of state EITC benefits.

[4]I calculate the age adjusted state level mortality rate by aggregating the population and death counts from the county level to the state level

4 Empirical Framework

4.1 Difference-in-Differences Approach

I estimate the effect of paid sick leave mandates on nursing home staffing and patient outcomes using a difference-in-differences identification strategy which exploits the temporal and geographic variation in the enactment of PSL mandates. The relationship between PSL mandates and my outcomes of interest are formalized as follows:

$$Y_{ft} = \alpha_{+}\gamma PSL_{ft} + \theta Z_{ct} + \beta X_{ft} + \delta_f + \mu_t + \epsilon_{ft} \tag{2}$$

PSL is an indicator for the enactment of a PSL mandate in year t[5], X is a vector of facility level characteristics (average resident age, for profit or non-profit, chain or single establishment, total number of beds, percentage of female residents, percentage of Medicaid payors), Z is a vector of time-varying county-level factors (unemployment rate, elderly share of the population, share of state SSI recipients who are elderly, AFDC and TANF caseloads, minimum wages, state EITC rate, and degree of competition among nursing home), δ_f is a facility fixed effect, and μ_t is a year fixed effect. In my sample PSL mandates are enacted at the city, state and county level. Hence, I define my variable at the establishment level. This represents a standard difference-in-differences analysis where outcomes in my treatment regions (i.e., counties and states enacting a PSL mandate) are compared to control regions that have no PSL laws in place. I cluster my standard errors at the county level in all analyses. My dependent variable, Y_{ft} in Equation (2) represents one of several possible outcomes in nursing homes.

I find that PSL laws increase the likelihood of firms exiting the market only slightly. This suggests to an extent that my findings are not driven by low-performing firms exiting the market. The main assumption under which my identification rests is that the trends in outcomes among facilities not receiving the treatment are accurately measuring counterfactual trends among the treated facilities. Figures 1, 2, and 3 present event study analyses from the three main groups

[5]I define enactment of a PSL mandate as the year in which the mandate actually took effect

of outcome variables. These figures provide visual evidence of an absence of pre-trends. This lends support to my difference-in-differences identification strategy.

4.2 The Synthetic Control Group Method

To assess the causal effect of sick pay mandates on nursing home elderly mortality rate I use the SCGM developed by Abadie and Gardeazabal (2003). The all county multiple cause of death Vital statistics micro data does not identify the specific nursing facility where the deceased passed away. Hence, my analysis for this outcome variable happens at an aggregated geographic level of either the county or the state level. This creates an ideal setup for an analysis using the SCGM. The SCGM creates a weighted average of multiple control units to create a synthetic control group whose prereform outcome exactly matches that of the treatment group (Abadie et al., 2010). Given certain assumptions hold, the differences in postreform outcomes between the treatment and the synthetic control group yields evidence on causal reform effects (Athey and Imbens, 2017).

In this study, following Appendix Table A4, the treatment units are counties or states that implemented sick pay mandates before 2015; the potential control units consist of the remaining U.S. counties or states. Because I analyze each treatment unit separately, the notation below refers to a single treatment and J control units.

Let y^0_{it} denote the outcome that would have been observed in region i at time t in the absence of the sick pay mandate. Moreover, y^1_{it} denotes the outcome for the treated region i at time t, where the sick pay mandate was implemented at time $T_0 + 1$. I assume $y^1_{it} = y^0_{it} \forall t = 1, ..., T0, \forall i = 1, ..., J + 1$.

According to (Abadie et al., 2010) the counterfactual y^0_{it} is represented by the following factor model:

$$y^0_{it} = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it} \tag{3}$$

where δ_t is a common time effect, θ_t is a vector of possibly time-dependent coefficients, λ_t

is a vector of unobserved common factors, and μ_i is a vector of unknown factor loadings.

The first assumption relevant to synthetic control methods requires that mortality rates in control regions are not affected by the treatment. This implies the absence of spatial spillover effects. In my analysis two of three treated states have donor states contributing to the synthetic control group that are neighboring states. Table A5 lists the donor states used to generate the synthetic control unit for each treated state. The table shows that the state of Nevada and the state of New Hampshire both contribute less than 10 percent (1.8 percent and 8.6 percent respectively) to the treated states of California and Massachusetts.

Second, similar to traditional difference-in-differences models, no unobserved shocks should affect the outcome differently for treatment and control groups in postreform periods. In this case, shocks violating this assumption would be other policies that are correlated with sick pay mandates in treated regions (but not in control regions). The SCGM may be more suitable than traditional methods in incorporating these shocks as the synthetic control units are, by construction, built to mimic the outcome of the treated unit (which includes unobservables affecting the outcome).

4.2.1 Implementation

SCGM requires the estimation of two matrices: 1) V is the weighting matrix determining the relative predictive power of Z_i and of y^0_{it} , and 2) W is a vector of nonnegative weights attached to the J control countries. The criterion to be minimized is

$$\|\bar{X}_1 - \bar{X}_0 W\|_V = \sqrt{(\bar{X}_1 - \bar{X}_0 W)' V (\bar{X}_1 - \bar{X}_0 W)}, \tag{4}$$

where $\bar{X}_1$ and $\bar{X}_0$ are vectors of averages over the pretreatment elements of Z_i and y_i for treated and control units, respectively.

I follow the literature and calculate the weighting matrix by minimizing the mean squared prediction error (MSPE) for prereform periods:

$$MSPE = \frac{\Sigma_t (y_t^1 - y_t^0 W^*(V))^2}{T_0} \tag{5}$$

where T_0 represents the number of prereform time periods.

4.2.2 Treatment Effects and Inference

Following (Abadie et al., 2010) I calculate both the pre and postreform MSPE and calculate the ratio between the two. The ratio between the post and pre reform MSPE indicates the size of a possible treatment effect. As the MSPE ratio is a measure of the relative treatment effect, I also calculate a percentage and level treatment effect.

I run placebo estimates as suggested by Abadie et al. (2010) to conduct inference. I construct placebo estimates for each treated unit I have considered in my SCGM analysis. I follow Abadie et al. (2010), and use the rank of the true treatment estimate relative to the N placebo estimates to determine the p-value of the H_0 hypothesis of no treatment effect ($H_0 : MSPERatio_{Treat} \leq MSPERatio_{Placebo}$). This can also be thought of as a percentile rank $p = \hat{F}(MSPERatio_e)$ for the event e, where $\hat{F}$ stands for the empirical cumulative distribution of all MSPE Ratios, from the placebo estimates. I use all the individual p-values and follow the procedure used by Dube and Zipperer (2015) to calculate joint p-values based on the sum of the single p-values using the Irwin-Hall distribution.

5 Results

5.1 Staffing

Recent literature has focused on the impact of PSL mandates in the United States on employment, however, to my knowledge there aren't any papers focusing on this particular market. Using staffing data from the CMS nursing home compare and ltc focus from the Brown School of Public Health (2020), I calculate the effect of PSL mandates on nursing home staffing. I present results for nursing assistant hours per resident day, and the total weekly hours by employee type per resident.

Table 3 reports a statistically significant increase in nursing assistant hours per resident day, driven by increases in part time nursing assistant hours. I find a very slight and statistically insignificant decrease in weekly hours of full-time nursing assistants per resident. I estimate that mandated PSL leads to a 0.356 unit increase in weekly part-time nursing assistant hours per resident in nursing homes on average, and a 0.035 unit increase in weekly hours for contract workers. Compared to baseline estimates this corresponds to around a 12 percent increase in weekly hours of part time workers per resident and an almost 20 percent increase for contract workers. This drives the 2.3 percent increase in nursing assistant hours per resident day which I find. Increased availability of sick time may lead to nursing assistants taking more time off, which may reduce attendance. Nursing homes thus may want to have a cushion for potential nursing assistant leave taking by increasing part-time nursing assistant hiring. As part-time nursing assistants accrue leave at a lower rate and in general have lower privileges, this may be a way nursing homes try to counter potential staffing decreases due to leave taking. Employers may also be looking to reduce over-time hours by hiring part time staff, thus trying to offset possible increases in cost caused by the PSL mandates. No significant changes in the full-time nursing assistant hours may be due to reduced sickness related leave taking by other staff not being infected due to presenteeism behavior of sick workers. The increased presence of part time nursing staff, along with no changes in other staff lead to significant improvements in the net hours per resident per day. Higher hours per resident day are a clear sign of improved quality at nursing homes.

5.2 Patient safety

As PSL mandates lead to increased time spent with patients and higher part-time and contract nursing assistant hours, it is likely that they may improve patient outcomes.

Panel A of Table 4 shows that PSL mandates significantly reduce the number of severe violations. The results from the table translate to a 7 percent reduction in the number of severe violations. Panel B reports an 8.5 percent reduction in number of severe quality of care violations. Similarly, existing literature on the effect of other policies on patient health show that higher minimum wages and increases in Medicare reimbursement rates in the early 2000's, reduced the number of violations and the likelihood of violations (Ruffini, 2020). My results are also similar to other studies finding changes in staffing through turnover (Antwi and Bowblis, 2018) and local unemployment (Huang et al., 2019), resulting in a significant reduction in the number of deficiencies in a nursing home.

5.3 Patient health

Tables 3 and 4 point to improved staffing outcomes and a reduction in the number of severe deficiencies. Improvements in quality along these measures are usually expected to be associated with improved patient health measures. To explore this argument, I analyze several measures of patient health which facilities submit to CMS every quarter. Previous literature points to the fact that these measures have a strong relationship to service quality provided by direct care staff (Brandeis et al. (1994); Dorr et al. (2005); Cawley et al. (2006); Grabowski et al. (2011)). More than 5 percent of residents in my sample have pressure ulcers, a preventable health condition. As nursing assistants help residents with day to day activities and monitor their health, close attention can reduce the likelihood of developing ulcers. Column (1) of Table 5 reports that PSL mandates reduce the share of residents with pressure ulcers by 0.6 percentage points, which translates to an almost 12 percent reduction in the share of pressure ulcers compared to baseline estimates.

The modal cause of bacterial-related hospitalization among nursing home residents are UTIs. Nursing assistants administer and monitor indwelling catheters, which frequently cause UTIs. Timely removal and minimizing usage of these devices can reduce the likelihood of infection (Saint (2000), CDC (2009)). From columns (3) and (4), I find that PSL mandates bring down the likelihood of UTI's by a negligible amount.

Existing literature does not point to a clear direction in which nursing homes change the usage of physical restraints in response to higher staffing costs. However, following the results from previous tables it may be the case that nursing homes are also providing better care along this dimension. Conversely, nursing homes may also be looking to offset increased costs from PSL by increasing the use of physical restraints. As physical restraints reduce movement, greater nursing assistant presence should reduce their usage (Cawley et al., 2006). Increased staff presence or assembly can also increase the use of these devices (Grabowski et al., 2011). Column (5) looks at the relationship between PSL mandates and physical restraint usage. I find that PSL mandates increase the usage of physical restraints by 0.8 units which translate to a 35 percent increase in usage compared to baseline estimates.

Anti-psychotic medications are often used as a form chemical restraint on residents with behavioral problems. They were introduced as a quality measure beginning in 2011 and hence have a restricted analysis sample. These drugs are primarily sedative which may have strong effects on patient's mental processes. In 2008 the FDA issued a warning that all anti-psychotics are associated with increased risk of death for persons with dementia. In, 2012 the CMS started a three pronged strategy to reduce the unnecessary use of anti-psychotics by initiating a national partnership with providers, launching an educational website, and public reporting of data on antipsychotic use. Existing literature has found higher licensed nurse staffing leads to reduced usage of anti-psychotic medication (Grabowski et al., 2011). Column (7) reports that PSL mandates reduce usage of anti-psychotic medication by 5 percent compared to baseline estimates.

Nursing homes often manage resident's behavioral health problems by using a combination of labor, medications, and physical restraints. It is widely believed that anti-psychotic medications are a substitute for nursing care, while physical restraint usually require more attention. My findings of higher staffing numbers along with lower usage psychotropic drugs and higher share of patients with restraints are in line with Grabowski et al. (2011), where they show a 10 percent increase in wages lead to an increase in psychotropic usage between 1.1 percent to 3.5 percent and a decrease in physical restraints between 26 percent and 28 percent.

5.4 Mortality

Higher mortality can be an extreme negative consequence of poor health conditions of nursing homes. Nursing home residents have a much higher mortality rate than that of the general population of the same age. One third of nursing home residents die within the first year of nursing home admittance, about three times the rate of the general population aged over 85. The results from my SCGM analysis on age adjusted elderly nursing home mortality rate are shown in Figures 4 and 5, and Table 6.

The left column of Figure 4 shows the evolution of state level elderly nursing home mortality rate in three treatment states and county level elderly nursing home mortality rate with the five boroughs of New York City aggregated as one treatment county. In the left column of Figure 4, the solid lines represent the treatment areas and the dashed lines represent the synthetic control areas. The composition of each treatment state- the weights W of the J control states- are in Table A5. The solid vertical line on the x-axis represents the year when the sick pay mandate went into effect.

The right column of Figure 4 displays the permutation inference using placebo tests graphically. Following the convention in the literature, the graphs plot the differences in the mortality rate (solid black) along with the differences for all placebo SCGM runs (gray). As seen, for prereform periods, the solid black line fluctuates very closely around the horizontal zero line implying that the synthetic control units very closely map the mortality rate of the treatment units. After the reform, which is indicated by the black dashed vertical line, mortality rate differentials between treated and control areas separate and the treated areas show a persistent negative difference with the synthetic group. One exception is New York City, where I witness an initial drop followed by a slight rise above the synthetic group. New York City is different from the other treatment areas in my analysis, the treatment area is completely urban, orders of magnitude denser in population, and the mortality rate is at a much lower baseline level.

Figure 4 and Table 6 show, substantial differences in mortality rate between treatment areas. Column (1) of Table 6 shows New York City has an average prereform mortality rate of 0.007, where as Massachusetts has a prereform mortality rate of 0.016. The pretreatment elderly nursing home mortality rate of the treatment areas closely match those of the synthetic control areas, providing support that SCGM produces valid counterfactuals. Visually, I also find sizeable and systematic reform related drops in the elderly nursing home mortality rate in the treated states. The mortality rate of treatment states appears to differ substantially from the mortality rate of synthetic control states. The pretreatment outcome dynamics of New York City has a closer match with its synthetic control group than the treated states. The SCGM analysis of New York City is at the county level and uses a donor pool of 100 counties resulting in a wider set of potential outcomes to create a weighted synthetic group from.

The left column of figure 5 shows, the difference between the treated and the synthetic control group's postreform mortality rate to be substantial for all the treated states. The right column of Figure 5 provides a visual exhibition of the procedure I use to conduct inference, following Abadie et al. (2010). After plotting the ratio of postreform MSPE to prereform MSPE of the treated and donor areas in descending order from the top, I find all treated states to be among top 5 units with Massachusetts having a rank of 1.

To quantitatively evaluate the SCGM fit between treated and controls, and to conduct inference, I show all relevant results in Table 6. Column (2) of Table 6 shows the ratio of post treatment MSPE to the pre treatment MSPE. The MSPE ratios lie between 10 for California and 61 for Massachusetts. I conduct inference using the method described in Section 4.2.2. For the states I use all never treated states between 2000 and 2018 as my donor states. Additionally, I drop the state of New York from the state level analysis as New York City makes up 43 percent of the population of the state. For New York City I choose 100 counties that provide the best prereform fit from all the never treated counties. To conduct inference, I replicate the standard SCGM procedure with each placebo state or county pretending it had been treated at the same time as the real treatment county or state. Column (5) illustrates the calculation of the p-values for the hypothesis $H0 : MSPERatio_{Treat} \leq MSPERatio_{Placebo}$, which is simply the rank of the MSPE Ratio of the treated county or state divided by #Total Counties/States Assessed. As seen in Column (4) except for California (p=0.125) all treatment areas are statistically significant with Massachusetts having a p-value of 0.025.

I also calculate the sum of all p-values and then evaluate their joint p-value based on the Irwin-Hall distribution (Dube and Zipperer, 2015). I find a highly precise joint p-value for the effect of paid sick leave mandates on elderly nursing home mortality rate. Column (4) of Table 6 shows the percentage treatment effect for each treatment unit and the average for all treated units. As seen in the figures, all 3 treated states have strong negative treatment effects with Massachusetts having a treatment effect of 8 percent. My results show a combined average negative treatment effect of 5.5 percent on elderly nursing home mortality[6]. My estimates are slightly larger than other labor market changes affecting nursing home mortality. For example, a 10 percent increase in minimum wage reduces nursing home mortality by 3.1 percent (Ruffini, 2020) and a 1 percentage point increase in the unemployment rate decreases nursing home mortality by 4.7 percent (Stevens et al., 2015). Column (5) of Table 6 shows the level treatment effect of elderly nursing home mortality rate for the postintervention periods. Column (6) of Table 6 lists the percentage difference in mortality rate between the treatment and the synthetic group in the year of 2016. Values from Column (6) are then used in Column (7) to calculate the net change in elderly nursing home deaths for each treatment area. I find that paid sick leave laws in the selected areas prevented an estimated 4479 deaths in total, with the bulk of reductions coming from Massachusetts and California.

5.5 Patient composition

If nursing homes change the composition of residents, it may have significant social welfare implications. Nursing homes may decide to offset increased costs borne from PSL mandates by increasing the share of patients from relatively wealthy private-paying sources. Medicaid reimbursement rates are lower than private-paying rates which are in turn lower than Medicare rates. In Table (7) and (8), I look at the effect of PSL mandates on the characteristics of admitted residents. Columns (1) and (2) of panel A in Table 7 show that PSL mandates do

[6] Results displayed in Appendix Table A6 shows the average percentage treatment effect increasing only slightly to 5.8 percent after adding King County, WA and San Francisco County, CA

not lead nursing homes to significantly change the share of residents who pay via Medicare or Medicaid. I find that PSL mandates lead to an increase in the share of private paying residents by 5.3 percent. I do find increases in the percentage of residents with higher average care needs, shown here by the assisted daily living index and average care index, which go up 2 percent and 1.7 percent respectively. Higher labor costs may lead to changes in facilities discharge or admission practices. Facilities may cycle through patients by sending them to the hospital and then readmitting them to the facility there by gathering higher Medicare reimbursement fees. Column (4) of Table 7 shows that facilities do not respond to PSL mandates by increasing resident churn. I do not see significant increases in occupancy rates after the enactment of PSL mandates.

Table 8 looks at effects on patient demographics and care needs, with Columns (1) and (2) showing characteristics that cannot be influenced by admission decisions. I also find a significant reduction in the share of female residents by almost 1 percent. I find that nursing homes have a slightly healthier composition of patients, with fewer hospital admits by 1.1 percent. Columns (3)-(6) look at care needs that can be altered by assessor judgment. I find favorable changes in care mix for residents, with the share with bladder incontinence going down significantly by 3.5 percent.

5.6 Heterogeneity

Average effects of the PSL mandate may be hiding the presence of heterogeneous effects. In tables 9, 10 and 11 I look at the effect on health outcomes, violations, and staffing by splitting the sample by profit status, multi-facility, and the share of residents paying via Medicaid. Table 9 looks at the effect of PSL mandates on resident health measures, by facility type. I do not find any heterogeneous effects on the share of residents with pressure ulcers and physical restraint use by facility type. For-profit and high-Medicaid share nursing homes show large drops in the share of residents on anti-psyhotic medications.

Panel A of Table 10 does show that the reductions in severe violations are driven by facilities with a higher share of patients paying via Medicaid. Nursing homes with a high share of

Medicaid paying residents show a more than 10 percent drop in the number of severe violations, almost ten times that of those with a low share of Medicaid payors. Panel B reports that the decreases in the number of severe care violations is driven by chain nursing homes. Multi-establishment nursing homes see a more than 15 percent reduction in the number of severe quality of care violations. Table 11 shows that increases in nursing assistant hours per resident day are significant in for-profit, multi-establishment, and high-medicaid facilities. The estimates are much stronger for these types of facilities. Additionally, high-Medicaid facilities show a 2.6 percent increase in the hours per resident day.

Residents paying through medicaid provide lower revenues and smaller margins. This may also make them more likely to be present in lower-quality nursing homes. My data does not allow me to identify whether the high-Medicaid share nursing homes provided paid sick leave to their employees or not. However, if that is actually the case, PSL mandates may actually be benefiting the low-income group of an already vulnerable population. Existing literature finds for-profit nursing homes driving improved deficiency scores and lower deficiencies in times of higher unemployment rate (Huang et al., 2019). For-profit and higher-Medicaid share nursing homes were also more likely to be found to have deficiencies in the existing literature (Harrington et al., 2000).

6 Robustness checks

A potential confounding factor is that higher labor costs may cause low-performing firms to exit the market. If low performing establishments were to exit the market, this would attenuate the aggregate benefits of PSL mandates. I construct a balanced panel of facilities that appear at any point in time in my sample and use my main regression equation with an outcome variable being an indicator equal to 1 if that facility appears in that given year. Table 12 shows that there is a slight (1.9 percent) reduction in likelihood that a facility exists after the introduction of PSL mandates. The precision and size of the estimates lend support to my estimates not being driven by the exit of low performing firms.

PSL mandates are much more likely to be enacted in areas passing a number of other labor reforms. Minimum wage is one such reform which has been shown in the literature (Ruffini, 2020) to affect nursing assistant performance. Table 12 shows evidence of contemporaneous increases in minimum wage along with paid sick leave mandates. A rough bounding exercise shows that my estimates are quite strong in spite of these changes. Literature finds a 10 percent increase in minimum wage to reduce the share of pressure ulcers by 1.4 percent (Ruffini, 2020). The extent to which this drives my result is about 14 percent. The estimates for other health measures and staffing hours remain strong after similar bounding exercises.

The main assumption for my identification is that the trends in outcomes among facilities not receiving the treatment are accurately measuring counterfactual trends among the treated facilities. I provide evidence via event study models that this assumption holds in the data. I run event study analyses that are depicted in Figures (1) through (3). I use the timing of enactment of the PSL mandates to carry out an event study analysis of the main outcome variables. This regression model also allows me to assess whether PSL mandates lead to an on-impact change in outcomes. The event studies are generalized difference-in-differences models similar to Jacobson et al. (1993). Instead of my regular difference-in-differences specification, I use dummy variables for each period before and after enactment of the laws for a maximum of 4 periods on either side (leaving out the period before enactment). I do not find any strong indications for presence of preexisting trends for my assessed outcome variables. This lends support to my difference-in-differences identification strategy. Figures 1 and 2 show the effects of the mandates on health and staffing outcomes persist long after enactment.

I estimate the effect of PSL mandates on a large number of nursing home outcome variables. It is plausible that some of these variables maybe correlated with one another. This creates the issue of multiple hypothesis testing. I provide evidence through Bon-ferroni and Sidak p-values that my outcomes are mostly robust to problems of multi collinearity. The p-values are provided in Appendix Tables A1 to A3. The health outcomes and staffing variables are highly significant, while the number of severe violations is just insignificant at the 10 percent level. These p-values are conservative measures and I expect my estimates to be precise to a large extent.

7 Conclusion

This paper finds that state mandated PSL leads to changes in nursing home staffing, and patient well-being. The estimates are precise and meaningful. Nursing homes may be increasing the number of part time nursing assistants to tackle possible increases in leave taking by full time staff. However, I do not witness any significant decreases in full time nursing assistant hours, which combined with increased part time hours lead to a net increase in staff hours per resident. Nursing homes also show improvements in patient health and safety, particularly reductions in the share of patients with pressure ulcers and severe violations. Nursing homes also substitute towards more attentive and less potentially harmful means of care for elderly patients. These results are mostly driven by high-Medicaid share nursing homes. Additionally, I find sharp and persistent decreases in nursing home elderly mortality rate after enactment of PSL mandates. My calculations show PSL mandates prevented about 4000 elderly nursing home deaths.

Nursing assistants may also be more attentive and productive at work if PSL reduces their likelihood of showing up sick. Cost savings from improved patient outcomes can offset a significant amount of the increased cost due to PSL. As these mandates end up positively impacting vulnerable sections of society, they have large potential social welfare implications. Nursing assistants and Medicaid insurance holders are both more likely to come from low-income backgrounds and thus may receive greater welfare weights by the social planner. As the population of the United States ages, these policies will have significant ramifications.

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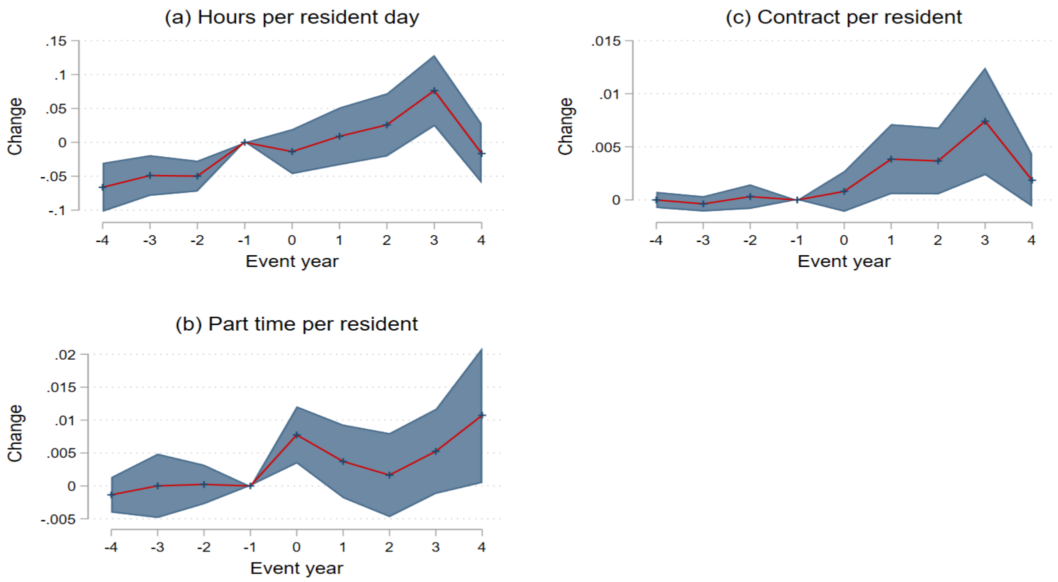
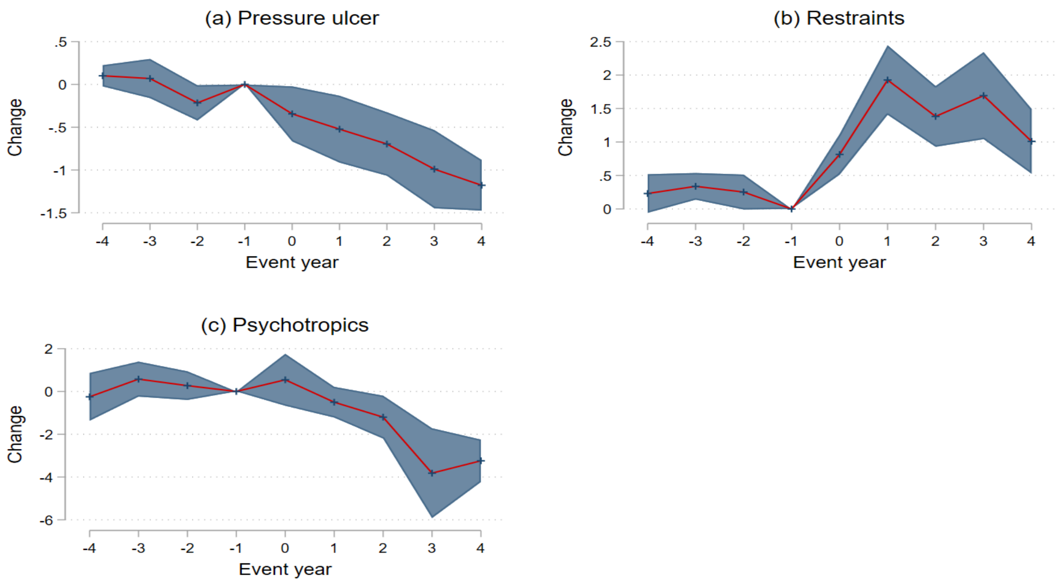
Figures

Figure 1: Staffing numbers event study



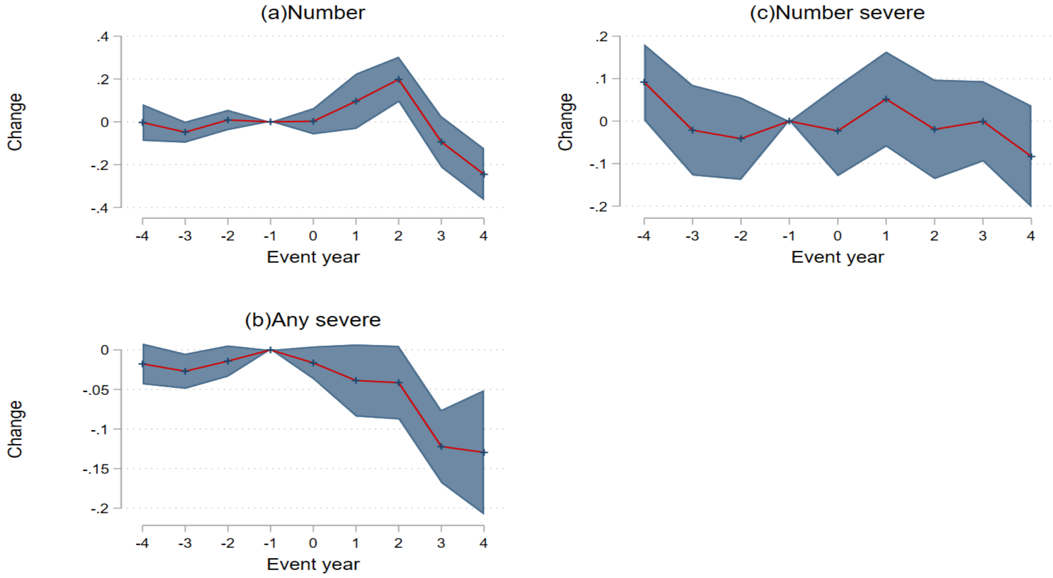
Note: Figure shows event studies with 4 prereform and 4 postreform periods. All specifications include controls for county employment rates and the elderly population share; state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; facility and year fixed effects; Shaded areas indicate 95 percent confidence intervals with robust standard errors clustered at the county level. Data from OSCAR/CASPER 2000-2018.

Figure 2: Patient health outcomes event study



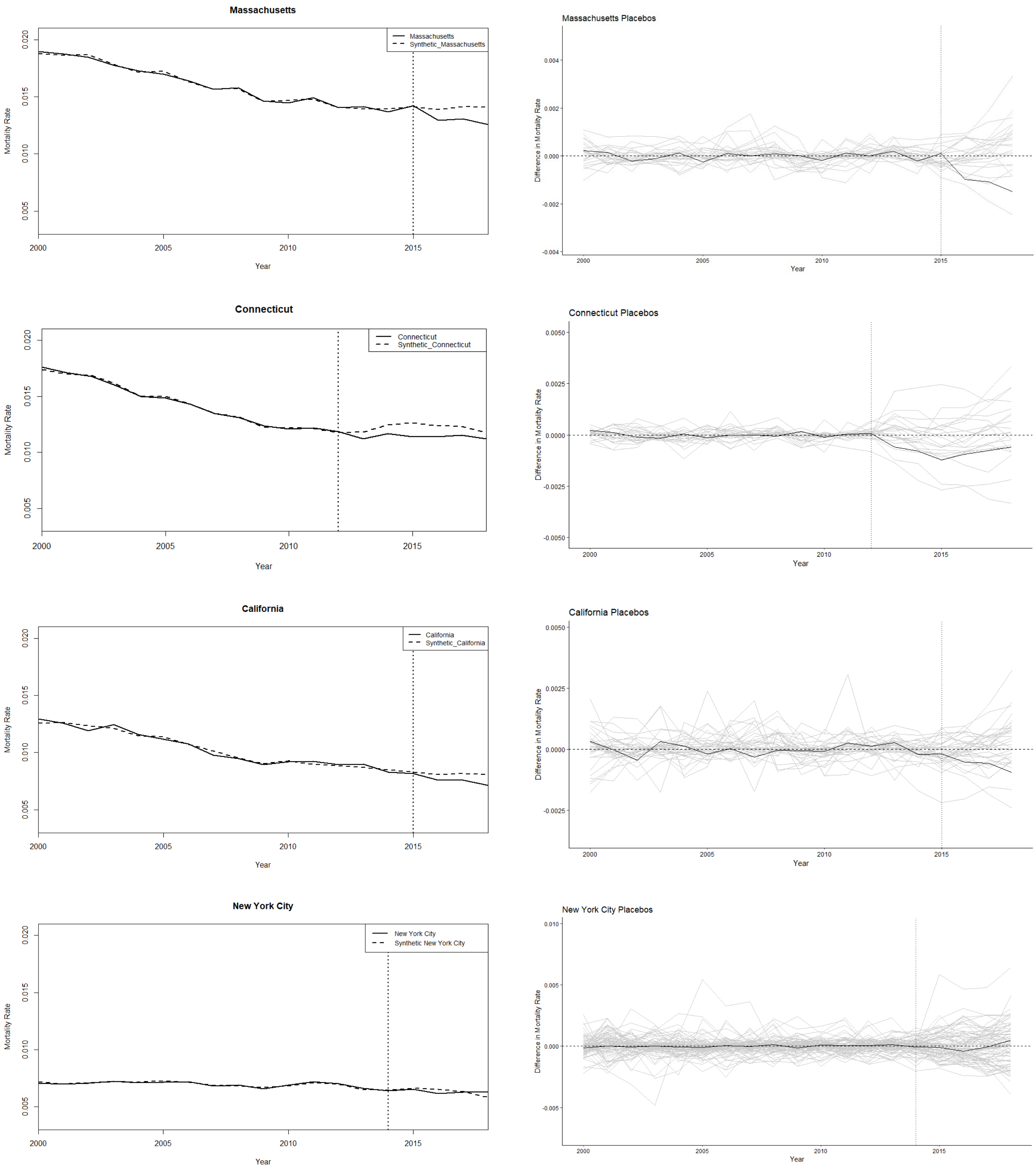
Note: Figure shows event studies with 4 prereform and 4 postreform periods. All specifications include controls for county employment rates and the elderly population share; state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; facility and year fixed effects; Shaded areas indicate 95 percent confidence intervals with robust standard errors clustered at the county level. Data from OSCAR/CASPER 2000-2018.

Figure 3: Violations event study



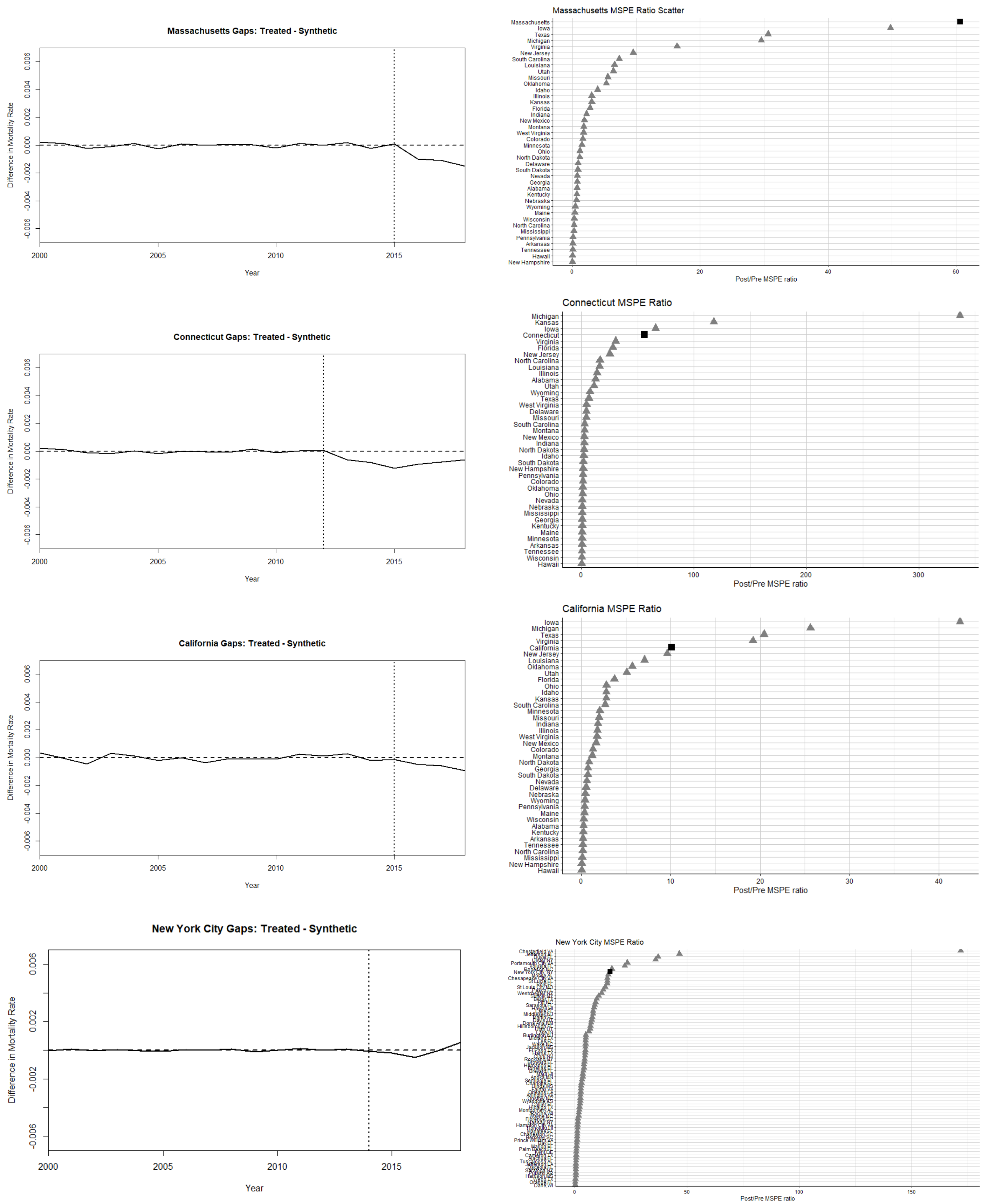
Note: Figure shows event studies with 4 prereform and 4 postreform periods. All specifications include controls for county employment rates and the elderly population share; state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; facility and year fixed effects; Shaded areas indicate 95 percent confidence intervals with robust standard errors clustered at the county level. Data from OSCAR/CASPER 2000-2018.

Figure 4: Mortality rate in treated vs synthetic control areas



Note: The left column compares treated areas (solid lines) to the synthetic control areas (dashed lines). The composition of the synthetic control states is in Table A4. The right column shows the difference in nursing home elderly mortality rate between treatment and synthetic control groups along with placebo estimates for never treated areas (gray lines). The dashed vertical line indicates when the law became effective. Source: Vital statistics all county mortality data.

Figure 5: Synthetic control method - treatment effect and inference



Note: The left column shows the difference in nursing home elderly mortality rate between the treatment and synthetic control group. The dashed vertical line indicates when the law became effective. The Source: Vital statistics all county mortality data. Right column plots the ratio of the post-reform MSPE to the pre-reform MSPE for the treatment area(black square) and the never treated areas (gray triangle).

Tables

Table 1: Overview of PSL mandates in the U.S.

(1)	(2)	(3)	(4)
Area	Law effective	hours accrued/40 hours	Benefit under law
San Francisco	Feb 5, 2007	1.33	b/w 5 to 9 days
Connecticut	Jan 1,2012	1	up to 5 days
Seattle, WA	Sep 1,2012	1 or 1.33	b/w to 13 days
New York, NY	April 1, 2014	1.33	up to 40 hours
Portland, OR	Jan 1 2014	1.33	up to 40 hours
Jersey City, NJ	Jan 22, 2014	1.33	up to 40 hours
Newark, NJ	May 29, 2014	1.33	b/w 24 to 40 hours
Philadelphia, PA	May 13, 2015	1	up to 40 hours
California	July 1, 2015	1.33	24 hours minimum
Massachusetts	July 1, 2015	1	up to 40 hours
Oregon	Jan 1, 2016	1.33	up to 40 hours
Montgomery county	Oct, 2016	1.33	b/w 32 to 56 hours
Arizona	July,2017	1.33	b/w 24 to 40 hours
Maryland	Feb,2018	1.33	up to 40 hours
Rhode Island	July, 2018	1.14	b/w 32 to 40 hours
Washington	Jan 2018	1	max carryover is 40 hours/year
Cook county, IL	July, 2017	1	up to 40 hours
Chicago, IL	July, 2017	1	up to 40 hours
Minneapolis	July, 2017	1.33	up to 48 hours
St. Paul	Jan, 2018	1.33	up to 48 hours
Vermont	Jan, 2017	0.77	b/w 24 and 40 hours
New Jersey	Oct 29, 2018	1.33	up to 40 hours

Table 2: Nursing home and area characteristics, by treatment

	(1)	(2)
	Control Areas	Treatment Areas
VARIABLES	mean	mean
AFDC/TANF maximum	435.9	723.9
% NH residents female	70.78	67.30
Avg NH resident age	80.67	78.85
% NH residents Medicaid	60.14	61.79
Minimum Wage	7.660	9.082
State EITC Rate	0.054	0.133
Avg facility size	103.8	116.1
County HHI	0.253	0.079
Any state EITC	0.410	0.520
Share popn > 65	0.151	0.132
Share state > 65 ssi recipients	0.020	0.047
Cty unemployment	6.001	6.697

Table 3: Nursing assistant staffing in Facilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Full time		Part time		Contract		Hours per	
	Weekly employee hours per resident						resident day	
Paid Sick Leave	-0.017	-0.011	0.356***	0.370***	0.035	0.041	0.053***	0.058***
	(0.019)	(0.020)	(0.071)	(0.073)	(0.047)	(0.052)	(0.016)	(0.017)
Observations	225,819	225,813	225,819	225,813	225,819	225,813	245,172	245,169
Number of establishments	16,401		16,401		16,401		16,563	
Establishment FE	YES		YES		YES		YES	
DV Mean	13.087	13.087	2.965	2.965	0.182	0.182	2.315	2.315

Note: Table shows the effect of mandated paid sick leave laws on nursing assistant staffing hours. I report results from the OSCAR/CASPER staffing reports reported by facilities to CMS, covering years 2000-2018 (columns 1-6)) and 2000-2018 (columns (7-8)). Hours per resident day is defined as the total weekly number of nursing assistant staffing hours times 35, divided by the number of residents times 7 (including direct care and administrative time). Full time employees defined as the number of nursing assistants typically working at least 35 hours a week; Part time employees defined as those typically working fewer than 35 hours a week. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels. Odd numbered columns include establishment fixed effects and even numbered columns county fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 4: Health inspection violations

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(number)		Any severe		Log(number severe)	
Panel A: All health violations						
Paid Sick Leave	0.03	0.023	-0.024	-0.026*	-0.073**	-0.092***
	(0.039)	(0.038)	(0.015)	(0.015)	(0.034)	(0.026)
Observations	201,807	201,804	201,807	201,804	201,807	201,804
Number of establishments	16,516		16,516		16,516	
Establishment FE	YES		YES		YES	
Panel B: Quality of care violations						
Paid Sick Leave	0.019	0.026	-0.011	-0.014	-0.089**	-0.102**
	(0.032)	(0.032)	(0.009)	(0.009)	(0.04)	(0.032)
Observations	201,807	201,804	201,807	201,804	201,807	201,804
Number of establishments	16,516		16,516		16,516	
Establishment FE	YES		YES		YES	

Note: Table shows results from the state health inspection reports reported to CMS, covering years 2000-2018. Severe violations are those presenting actual harm or immediate jeopardy to residents (CMS categories G-L). Quality of care violations follow the definition in Harrington et al. (2001) to include violations in the quality of care, assessment, nursing, dietary, physician, rehabilitative services, dental, and pharmacy regulation categories. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels. Odd numbered columns include establishment fixed effects and even numbered columns county fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 5: Patient Health Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Pressure ulcers		UTI		Restraints		Psychotropic	
Paid Sick Leave	-0.615***	-0.628***	0.017	-0.004	0.847***	1.008***	-1.091***	-1.024**
	(0.124)	(0.128)	(0.134)	(0.129)	(0.150)	(0.154)	(0.422)	(0.431)
Observations	169,640	169,637	175,026	175,023	175,153	175,150	92,859	92,851
Number of establishments	15,872		15,896		15,902		15,246	
Establishment FE	YES		YES		YES		YES	
DV Mean	5.225	5.225	6.370	6.370	2.419	2.419	19.27	19.27

Note: Table shows patient outcomes results from long-term resident assessment reports reported by facilities to CMS, covering years 2000- 2018. Reports for psychotropic medications available beginning 2005. All variables are winsorized at the 99th percentile to exclude extreme values. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels. Odd numbered columns include establishment fixed effects and even numbered columns county fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 6: Synthetic control group method-The effect of psl mandates on mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\bar{Y}^1_{i,pre}$	MSPE Ratio	Rank-MSPE/ #Placebos = P-value	Percentage Treatment Effect	Level Treatment Effect	Percentage Treatment Effect-2016	Change in Deaths w.r.t 2016
Areas							
New York City	0.007	16	0.079	-0.3	0	-6.1	-414
Connecticut	0.014	56	0.1	-6.6	-0.001	-7.6	-539
California	0.01	10	0.125	-7	0	-6.5	-2522
Massachusetts	0.016	61	0.025	-8	-0.001	-7.1	-1004
Average/Sum		36	0.329	-5.5	0	-6.8	-4479
P val Irwin Hall			0				

Note: Table shows elderly mortality rate from years 2000-2018 using data Vital Statistics all county microdata. The age adjustment, defined in Equation (1), holds the age composition of the population fixed at its 2010 distribution; see Stevens et al. (2015). All statistics displayed here are discussed in Section 5. Column (1) displays the outcome measure in levels for each treated area averaged over all prereform years. Column (2) displays the RMSPE Ratio [RMSPE post/RMSPE pre]. Column (3) calculates the p-value of the RMSPE Ratio for all treated areas using the indicated number of placebo estimates. Columns (4) and (5) show the Percentage treatment effect and Level treatment effect. Column (6) shows change in nursing home deaths with respect to total elderly nursing home deaths in the respective area in 2014. For the first treatment area, the synthetic control group method was applied at the county level with the five boroughs of New York City as 1 county representing the treatment area of New York City. For the remaining treatment areas a synthetic control method was applied at the state level.

Table 7: Payment methods and care needs

	(1)	(2)	(3)	(4)
Panel a:		Resident Share		
	Medicaid	Medicare	Other	Hospitalizations
Paid Sick Leave	-0.779	-0.534	1.313*	-0.00899
	(0.771)	(0.331)	(0.701)	(0.0202)
Observations	245,366	245,366	245,366	229,998
Number of establishments	16,569	16,569	16,569	16,492
DV Mean	60.60	14.83	24.57	0.967
Panel b:			Average resident care needs	
	Occupancy Rate	Successful Discharge	ADL index	Care index
Paid Sick Leave	0.241	-0.00513	0.320**	0.0159***
	(0.454)	(0.00316)	(0.127)	(0.00582)
Observations	245,203	93,943	245,365	245,365
Number of establishments	16,566	15,035	16,569	16,569
DV Mean	83.31	0.517	15.97	0.935

Note: Panel a of table shows the share of nursing home residents by payment source (columns (1) through (3)); Discharge, transfer, and occupancy rate (panel (a) column(4) and panel b column(1) and (2)) average standardized care needs (Panel (b) columns (3) and (4)); derived from resident assessment reports reported by facilities to CMS covering years 2000 through 2017, summarized in LTC focus. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; and establishment fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 8: Payment care needs and demographics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Patient demographics		Patient care needs		
	%	%	%	% Incontinence	% Incontinence
	Female	Hospital Admit	Hypertension	Bladder	Bowel
Paid Sick Leave	-0.693***	-0.888**	-1.057	-2.354***	-0.685
	(0.139)	(0.370)	(0.876)	(0.476)	(0.479)
Observations	245,414	230,292	238,394	241,618	232,080
Number of Provider	16,574	16,210	16,347	16,339	16,248
DV Mean	70.13	77.37	61.61	67.55	54.57

Note: Derived from resident assessment reports reported by facilities to CMS covering years 2000 through 2017, summarized in LTC focus. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; and establishment fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 9: Patient health outcome by provider characteristic

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Profit	Non -Profit	Multi -facility	Single	High medicaid	Low medicaid
			Panel a: Pressure ulcer			
Paid Sick Leave	-0.500***	-0.601***	-0.612***	-0.522***	-0.584***	-0.477***
	(0.134)	(0.161)	(0.148)	(0.162)	(0.148)	(0.143)
Observations	108,918	41,868	95,154	74,486	88,618	81,022
DV Mean	5.372	4.997	5.353	5.059	5.664	4.682
			Panel b: Restraints			
Paid Sick Leave	1.220***	0.441***	0.719***	1.171***	1.390***	0.478***
	(0.159)	(0.162)	(0.119)	(0.216)	(0.204)	(0.130)
Observations	112,676	43,623	97,900	77,253	91,340	83,813
Establishment FE	YES	YES	YES	YES	YES	YES
DV Mean	2.468	1.544	2.321	2.547	2.693	2.083
			Panel c: Psychotropics			
Paid Sick Leave	-0.994*	-0.565	-0.659**	-1.608***	-1.559***	-0.376
	(0.526)	(0.406)	(0.331)	(0.572)	(0.534)	(0.378)
Observations	65,957	26,902	52,897	39,962	47,176	45,683
Establishment FE	YES	YES	YES	YES	YES	YES
DV Mean	20.19	17.52	19.42	19.06	20.90	17.12

Note: Table shows patient outcomes results from long-term resident assessment reports reported by facilities to CMS, covering years 2000- 2018. Reports for psychotropic medications available beginning 2005. All variables are winsorized at the 99th percentile to exclude extreme values. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; and establishment fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 10: Violations by provider characteristic

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Profit	Non -Profit	Multi -facility	Single	High medicaid	Low medicaid
	Panel a: Log(Number of severe violations)					
Paid Sick Leave	-0.0739*	-0.115*	-0.0923*	-0.0743*	-0.112**	-0.0115
	(0.0424)	(0.0656)	(0.0497)	(0.0440)	(0.0441)	(0.0498)
Observations	21,671	8,288	19,020	14,129	18,031	15,118
Number of Provider	9,844	3,974	7,961	6,688	8,106	7,543
	Panel b: Log(number of severe care violations)					
Paid Sick Leave	-0.0998**	-0.203***	-0.166**	-0.0367	-0.0627	-0.0483
	(0.0457)	(0.0638)	(0.0669)	(0.0510)	(0.0605)	(0.0635)
Observations	15,510	5,729	13,779	9,827	12,927	10,679

Note: Table shows results from the state health inspection reports reported to CMS, covering years 2000-2018. Severe violations are those presenting actual harm or immediate jeopardy to residents (CMS categories G-L). Quality of care violations follow the definition in Harrington et al. (2001) to include violations in the quality of care, assessment, nursing, dietary, physician, rehabilitative services, dental, and pharmacy regulation categories. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; and establishment fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = p $<$ 0.01, ** = p $<$ 0.05, * = p $<$ 0.10.

Table 11: Nursing assistant staffing by provider characteristic

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Profit	Non -Profit	Multi -facility	Single	High medicaid	Low medicaid
			Panel b: Hours per resident day			
Paid Sick Leave	0.059***	0.009	0.061***	0.023	0.058***	0.033
	(0.018)	(0.025)	(0.020)	(0.019)	(0.018)	(0.021)
Observations	160,036	66,365	135,699	109,525	127,572	117,652
DV Mean	2.228	2.528	2.219	2.435	2.205	2.438

Note: I report results from the OSCAR/CASPER staffing reports reported by facilities to CMS, covering years 2000-2018 (columns 1-6)) and 2000-2018 (columns (7-8)). Hours per resident day is defined as the total weekly number of nursing assistant staffing hours times 35, divided by the number of residents times 7 (including direct care and administrative time). Full time employees defined as the number of nursing assistants typically working at least 35 hours a week; Part time employees defined as those typically working fewer than 35 hours a week. All specifications include controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels. Odd numbered columns include establishment fixed effects and even numbered columns county fixed effects. Demographic controls include average resident age, facility size, and the share of residents female, and covered by Medicaid. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 12: Robustness Checks

	(1)	(2)
VARIABLES	Presence	Minimum Wage
Paid sick leave	-0.0151*	0.850***
	(0.00793)	(0.0447)
Observations	345,309	54,424
DV Mean	0.767	7.701

Note: Specification includes controls for county employment rates and the elderly population share; and state EITC parameters, the share of the elderly population receiving Supplemental Security Income, and AFDC/TANF caseloads and benefit levels; and establishment fixed effects. Robust standard errors clustered by county. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Appendix

Table A1: Health outcome coefficients p-values adjusted for multi-collinearity

	(1)	(2)	(3)	(4)
VARIABLES	Pressure ulcer	UTI	Restrained	Psychotropic
Unadjusted P-value	0.000***	0.899	0.000***	0.01***
Bonferroni P-value	0.000***	0.899	0.000***	0.02**
Sidak P-value	0.000***	0.877	0.000***	0.019**

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Deficiencies p-values adjusted for multi-collinearity

	(1)	(2)	(3)	(4)	(5)	(6)
	Health violations			Care violations		
VARIABLES	#	Any severe	# severe	#	Any severe	# severe
Unadjusted P-value	0.441	0.082	0.019**	0.839	0.241	0.018**
Bonferroni P-value	0.883	0.327	0.105	0.883	0.722	0.105
Sidak P-value	0.688	0.289	0.101	0.839	0.562	0.101

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Nursing assistant staffing outcomes coefficients p-values adjusted for multi-collinearity

	(1)	(2)	(3)
VARIABLES	Full time	Part time	contract
Unadjusted P-value	0.164	0.001***	0.053*
Bonferroni P-value	0.164	0.004***	0.106
Sidak P-value	0.164	0.004***	0.103

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Detailed overview of paid sick leave mandates in the U.S. effective on or before 2015

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Area	County	No. of beds in area in 2014	Share of beds in county	Date Law Effective	hours accrued/40 hours	Benefit under law
San Francisco	SF	2636	100%	Feb 5, 2007	1.33	b/w 5 to 9 days
Seattle, WA	King	3292	53%	Sep 1,2012	1 or 1.33	b/w to 13 days
Portland	Multnomah	2526	84%	Jan 1, 2014	1.33	Up to 40 hours
Jersey City, NJ	Hudson	1062	40%	Jan 22, 2014	1.33	up to 40 hours
Newark, NJ	Essex	1148	24%	May 29, 2014	1.33	b/w 24 to 40 hours
Philadelphia, PA	Philadelphia	7258	100%	May 13, 2015	1	Up to 40 hours
New York, NY	Bronx, Kings Queens, New York Richmond	44849	100%	April 1, 2014	1.33	up to 40 hours
Connecticut		27671		Jan 1,2012	1	up to 5 days
Massachusetts		47517		July 1, 2015	1	up to 40 hours
California		117781		July 1, 2015	1.33	24 hours minimum

Table A5: States for synthetic control group

	Connecticut	California	Massachusetts
Colorado	0.289	0	0.214
Florida	0	0.414	0
Georgia	0	0.026	0
Hawaii	0.180	0	0
Illinois	0.001	0.039	0.161
Kentucky	0	0	0.001
Maine	0.046	0	0
Minnesota	0	0	0.080
Missouri	0	0	0.116
Nebraska	0	0	0.001
Nevada	0	0.018	0
New Hampshire	0.046	0	0.086
New Jersey	0	0.288	0
North Dakota	0	0.056	0
Ohio	0	0	0.153
Pennsylvania	0	0	0.112
South Dakota	0.173	0	0
Virginia	0	0	0.002
Utah	0	0.159	0
Wisconsin	0.265	0	0.072
...	...	...	...

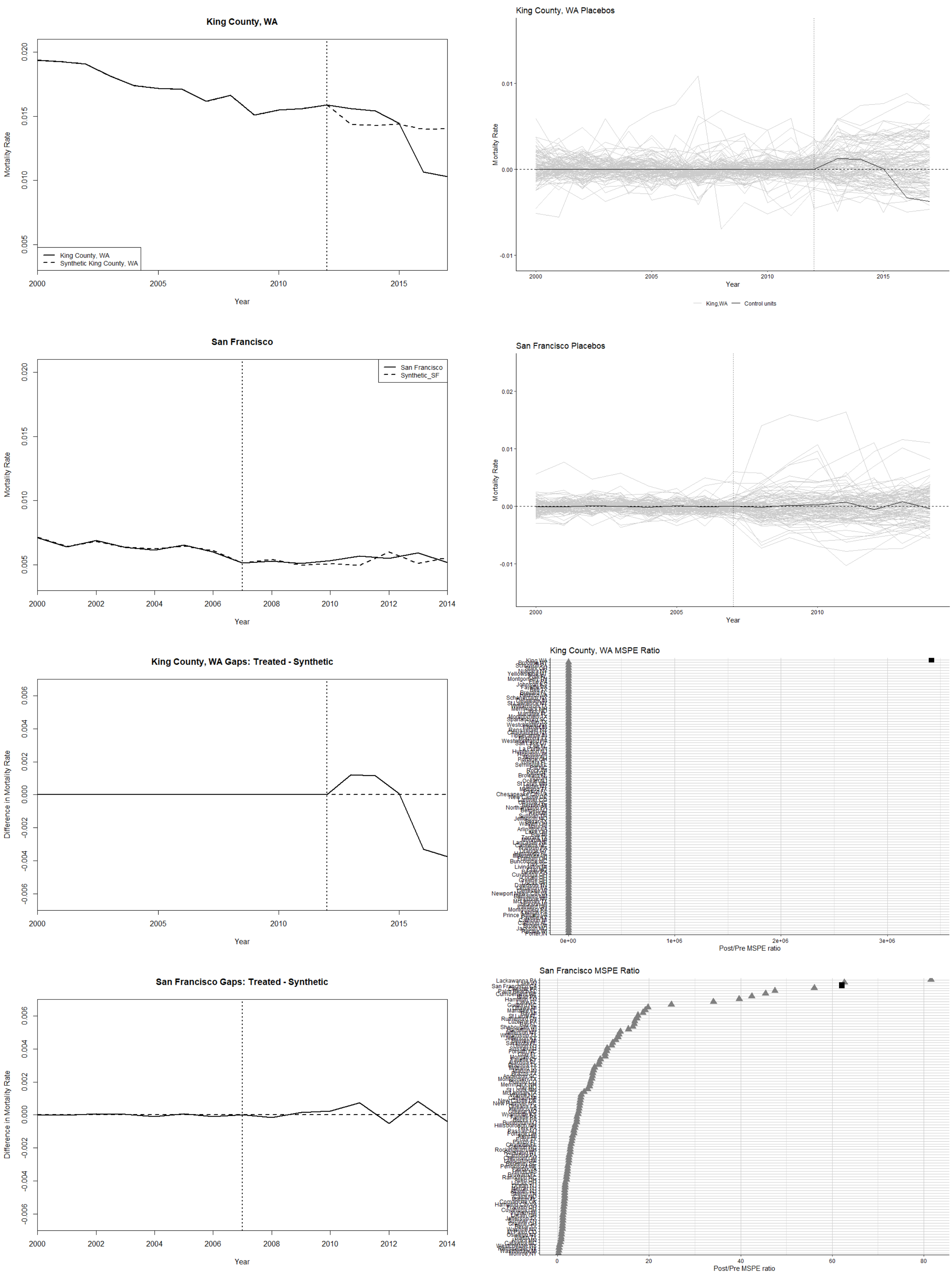
Note: The table shows the vector of weights W that minimizes the MSPE (see Equation (5)) for all treated states and nursing home elderly mortality rate as dependent variable. These weights are used to construct the synthetic control states in Figure 1 and Figure A1. The weights are also used to calculate the indicators in Table 6. ... represents the missing states (out of a total of 40). States which are potential donors, but, do not have positive weights for any treated state have been dropped from the table. All states with positive fractions indicate the donor share employed by the SCGM to replicate the treatment county in the column header. All fractions in one column add to 1. Source: Vital Statistics all county microdata.

Table A6: Synthetic control group method- nursing home elderly mortality rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\bar{Y}^1_{i,pre}$	MSPE Ratio	Rank-MSPE/ #Placebos = P-value	Percentage Treatment Effect	Level Treatment Effect	Percentage Treatment Effect-2016	Change in Deaths w.r.t 2016
Counties							
King County, WA	0.017	$3*10^6$	0.009	-6.5	-0.001	-23.6	-604
San Francisco, CA	0.006	62	0.03	2.4	0		
New York, NY	0.007	16	0.079	-0.3	0	-6.1	-414
Average/Sum		$1*10^6$	0.118	-1.5	0	-14.9	-1018
P val Irwin Hall			0				
States							
California	0.01	10	0.125	-7	0	-6.5	-2522
Massachusetts	0.016	61	0.025	-8	-0.001	-7.1	-1004
Connecticut	0.014	56	0.1	-6.6	-0.001	-7.6	-539
Average/Sum		42	0.25	-7.2	0	-7.1	-4065
P val Irwin Hall			0				
Total(All):							
Average/Sum		$5.6*10^5$	0.37	-4.4	0	-10.9	-5,083
P val Irwin Hall			0				

Note: Table shows nursing home elderly mortality rate from years 2000-2018 using data from Vital Statistics all county microdata. The age adjustment, defined in Equation 1, holds the age composition of the population fixed at its 2010 distribution; see Stevens et al. (2015). All statistics displayed here are discussed in Section 5. Column (1) displays the outcome measure in levels for each treated area averaged over all prereform years. Column (2) displays the MSPE Ratio [MSPE post/MSPE pre]. Column (3) calculates the p-value of the MSPE Ratio for all treated areas using the indicated number of placebo estimates. Columns (4) and (5) show the Percentage treatment effect and Level treatment effect. Column (6) shows change in nursing home deaths with respect to total elderly nursing home deaths in the area in 2014. Hudson county and Essex county are absent due to less than 50% of the beds in those two counties are part of the areas which passed the law, i.e Jersey City and Newark. Multnomah county is dropped because the state of Oregon's sick leave mandate came into effect in 2016. Philadelphia has been dropped due to there being a poor pre-reform fit. Due to California's mandate coming in to effect in 2015, San Francisco is plotted till 2014, and hence has a missing net death count for 2016.

Figure A1: Mortality rate in treated vs synthetic control areas



Note: The first two plots on the left compares treated areas to the synthetic areas. The first two plots on the right show the difference in mortality rate between treatment and synthetic group, and placebo estimates for donor counties (gray lines). The last two plots on the left column shows the difference in mortality rate between the treatment and synthetic group. The last two plots on the right column plots the ratio of the postreform MSPE to the prereform MSPE for treatment (black square) and control (gray triangle). The dashed vertical line indicates when the law became effective. Source: Vital statistics all county microdata. King County is plotted till 2017 as Washington's law came in to effect in 2018. San Francisco is plotted till 2014 as California's law came in to effect in 2015.