Population Mortality and Laws Encouraging Influenza Vaccination for Hospital Workers

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Background: Since 1995, 14 states have passed laws encouraging or mandating influenza vaccination for hospital workers. Although the Centers for Disease Control and Prevention recommends vaccinating health care workers to reduce disease transmission and patient risk, the effect of these laws on pneumonia and influenza mortality is unknown.

Objective: To measure the effect of state-level hospital worker influenza vaccination laws on pneumonia and influenza mortality.

Design: Quasi-experimental observational study.

Setting: United States.

Participants: Population of all states from 1995 to 2017.

Intervention: State adoption of a law promoting influenza vaccination for hospital workers.

Measurements: Pneumonia and influenza mortality per 100 000 persons by state and by month, both population-wide and separately by age group, obtained from restricted-access National Vital Statistics System files. Linear and log-linear models were used to compare changes in mortality rates for adopting versus nonadopting states.

Results: Implementation of state laws requiring hospitals to offer influenza vaccination to their employees was associated with a 2.5% reduction in the monthly pneumonia and influenza mortality rate (−0.16 deaths per 100 000 persons [95% CI, −0.29 to −0.02]; P = 0.022) during the years when the vaccine was well matched to the circulating strains. The largest effects occurred among elderly persons and during peak influenza months.

Limitation: Utilization of large-scale national data precluded analysis of more specific outcomes, such as laboratory-confirmed or hospital-acquired influenza.

Conclusion: State laws promoting hospital worker vaccination against influenza may be effective in preventing pneumonia- and influenza-related deaths, particularly among elderly persons. Vaccinating hospital workers may substantially reduce the spread of influenza and protect the most vulnerable populations.

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Pneumonia and influenza are the eighth leading cause of death in the United States. Seasonal influenza also represents a substantial economic burden, costing an estimated $11.2 billion annually (1, 2).

Seasonal influenza vaccines are a key defense against infection, but they can be less effective in elderly adults and chronically ill persons, for whom influenza poses the greatest danger (3). To reduce the spread of influenza viruses and protect these vulnerable groups, the Centers for Disease Control and Prevention (CDC) has long recommended vaccinating health care workers against influenza (4). Consistent with this recommendation, between 1995 and 2017, 13 states and the District of Columbia passed laws targeting hospital worker influenza vaccination (5). These laws generally require that hospitals provide influenza vaccination onsite for their employees, and more coercive policies mandate vaccination or require face masks to be worn by unvaccinated workers. Six of the 14 laws also extend to health care workers outside the hospital setting.

Although substantial literature has shown that offering influenza vaccines at health care workers' place of employment increases uptake (6–8), evidence that health care worker vaccination reduces influenza-related mortality or morbidity is sparse (9–11). Notably, none of the existing studies have had large enough study populations to detect effects on influenza-related deaths.

We aim to fill this gap in the literature with our analysis of state-level hospital worker influenza vaccination laws ("state laws") and population-level pneumonia and influenza mortality rates. We focus on mortality from both pneumonia and influenza because diagnosis codes for influenza infection are rarely used on death certificates, even when it is a contributing factor (11–13). Our analysis tests the hypothesis that these laws lead to reductions in virus transmission within and outside hospitals, thus reducing mortality in the overall population.

METHODS

Study Period and Design

Our study period spans 23 years, from 1995 through 2017. We used quasi-experimental, state-level, longitudinal designs to estimate the association of state laws with mortality rates. In one design, we conducted a synthetic control analysis to estimate a separate treatment effect for each of the 14 states (including the District of Columbia) that adopted a vaccination law between 2002 and 2014. In another design, we estimated an average treatment effect using a state-level, longitudinal model in which we controlled for national calendar-time fixed

See also:

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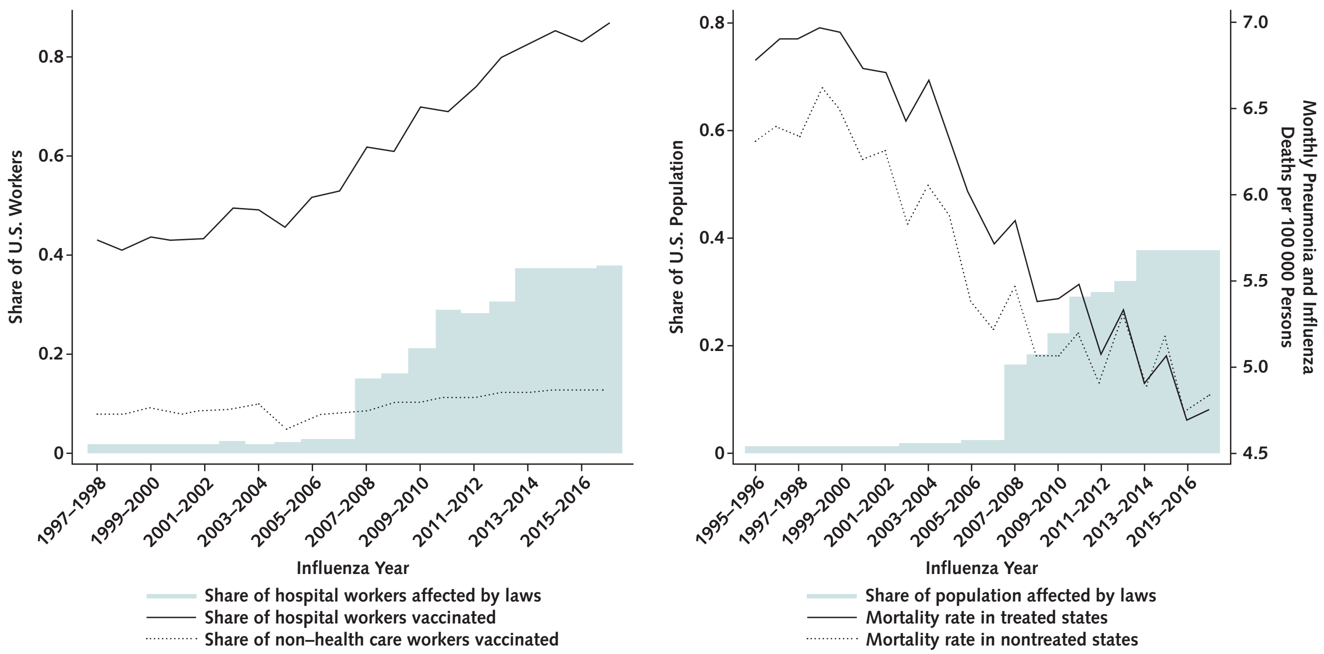
Supplement

Figure 1. Trends in influenza vaccination coverage and pneumonia and influenza mortality rates.



Left. Influenza vaccination coverage among employed adults and share of hospital employees subject to a state influenza law. Influenza vaccination data are from the IPUMS National Health Interview Survey database (17), 1997 to 2017 survey waves, and are based on the sample of employed adults. The variable capturing the share of U.S. hospital workers subject to a law in a given influenza year is constructed using data from the IPUMS Current Population Survey database, 1997 to 2017 survey waves (18). More details on the construction of this figure are provided in section 8 of the Supplement. **Right.** Pneumonia and influenza mortality rate in ever-adopting and never-adopting states and share of total population subject to a state influenza law. "Treated states" are the 14 states (including the District of Columbia) that ever had an influenza law during our sample period, and "non-treated states" are the remaining 36 states. The population share is the share of the U.S. population (i.e., not only hospital workers, as in the left panel) residing in a state with a law in each influenza year.

effects, state fixed effects, and state-specific time trends. Each of these approaches compared differences in mortality rates between states with and without laws in place, before and after law implementation.

Data and Study Variables

We collected information on the timing and content of state laws from the CDC Public Health Law Program's Menu of State Hospital Influenza Vaccination Laws and from our review of state statutes (14). Our primary independent variable was an indicator for whether any state law was in effect in a given state at a given point in time.

Our primary outcome was the pneumonia and influenza mortality rate per 100 000 persons, constructed from the National Vital Statistics System multiple cause-of-death microdata files. Covariates included binary variables for state laws regarding influenza vaccination in long-term care facilities and childcare centers. We used CDC data on the match between each season's vaccine with the circulating influenza virus strains for sample selection.

To depict national trends in hospital workers' vaccination coverage and exposure to state laws over our sample period, we used annual influenza vaccination rates by occupation from the National Health Interview Survey and hospital sector population data from the Current Population Survey (15, 16). We also used data from the Behavioral Risk Factor Surveillance System, the National Immunization Survey-Child, and the National Immunization Survey-Teen to examine state-level changes in adult, infant, and adolescent vaccination rates (section 1 of the **Supplement**, available at Annals.org) (17–19).

Study Population

National Vital Statistics System data report deaths in all 50 states and the District of Columbia. The population of the 14 states that enacted a vaccination law during our sample period was the exposed population; the population of all remaining states was the control population. All 14 state laws required influenza vaccines to be offered to hospital employees. In addition, 11 laws required workers to be vaccinated or to document their declination of the vaccine, and 3 of these laws mandated that employees who declined vaccination wear a surgical mask during influenza season (section 2 of the **Supplement**). Approximately 4% of hospitals in the United States are Veterans Health Administration facilities or other federal hospitals and are not bound by these state laws. Also, during this period, some hospitals independently adopted hospital-level vaccination policies, which we did not control for in this study.

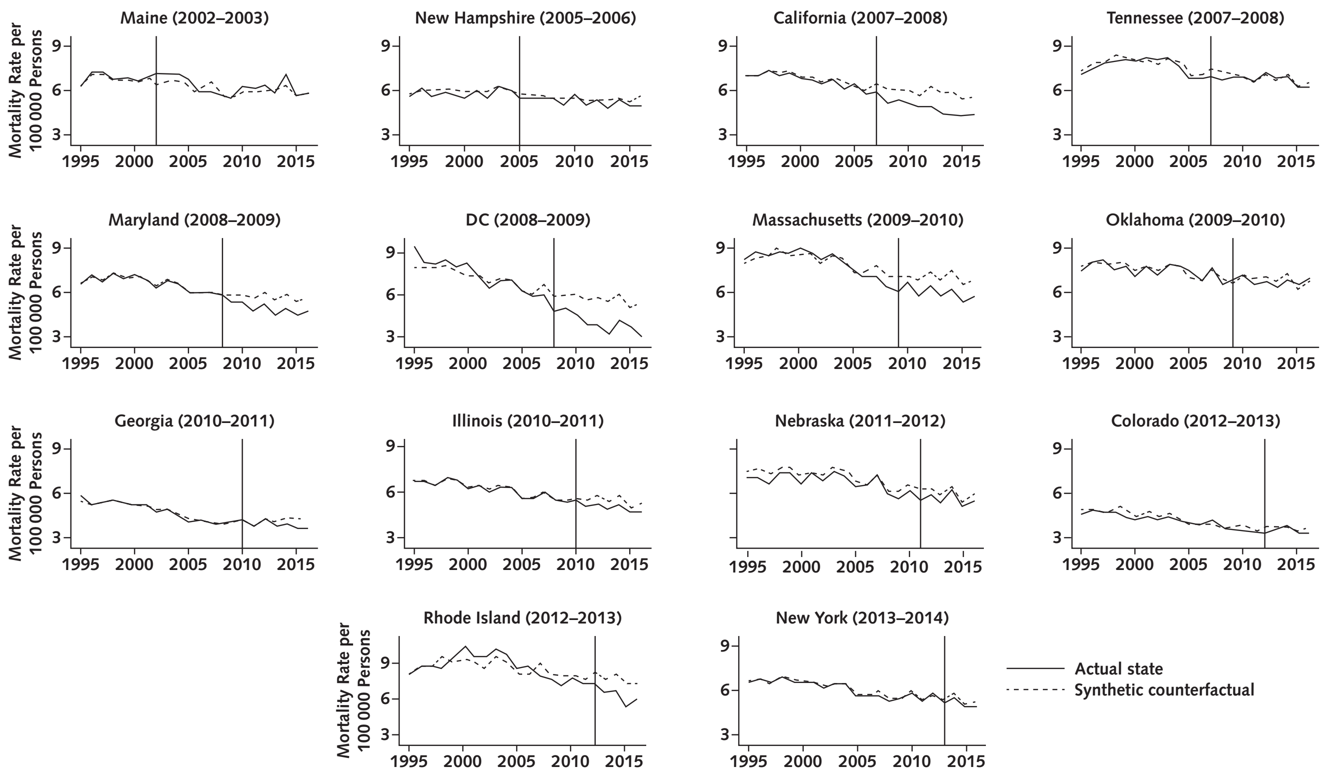
An influenza year spanned July to June to capture the full influenza season, and we studied the influenza years 1995–1996 through 2016–2017. Peak influenza months were December through March. The unit of analysis was the state-year-month level. Our main analyses were limited to 17 influenza years in which the vaccine was well matched to circulating strains (we excluded 5 influenza years with match rates below 50% [**Supplement Figure 5**, available at Annals.org]).

Statistical Analysis

We conducted all analyses using Stata/MP, version 14.0 (StataCorp). We examined the change in pneumonia and influenza mortality associated with hospital worker vaccination laws through 2 quasi-experimental approaches. In the first approach, we estimated a separate treatment effect for each of the adopting states by using a synthetic control analysis. For each adopting state, we constructed a synthetic counterfactual population from the set of states that never adopted a vaccination law (using the synth command in Stata) and estimated the reduction in the monthly log mortality rate in each state as the average treatment–control difference in the posttreatment period. To help interpret these results, we transformed them into the difference in the number of monthly pneumonia and influenza deaths per 100 000 persons by using the formula [exp(difference in logs) − 1] × [baseline mean pneumonia and influenza mortality rate per 100 000 persons]. We calculated *P* values using randomization inference based on the distribution of the ratio of posttreatment root mean squared prediction error (RMSPE) to pretreatment RMSPE (20). Therefore, a small *P* value requires a good pretreatment match in addition to large posttreatment differences (section 3 of the **Supplement**). This approach has limitations; a good pretreatment match may not be possible for all treated units, and the method for estimating average treatment effects when multiple states adopt laws at different times is not well established (21–23).

In the second approach, we implemented longitudinal models with 2-way fixed effects to estimate the average effect of state laws on mortality rate changes across all 14 states. We used linear regression to associate the natural log of the mortality rates with a variable that indicated whether a law was in effect in a given state and influenza year. To control for time-varying factors that are common to all states, such as seasonality, we used fixed effects based on year and month (for example, January 2015). To control for time-invariant factors that differ across states, we used fixed effects specific to each state. We also included state-specific time trends. Therefore, the coefficient for the variable indicating the presence of a law measured the average change in the log mortality rate from the years before versus the years after implementation for states that adopted laws, net of the average change in nonimplementing states and the expected trajectories based on state time trends. We transformed the

Figure 2. Trends in the pneumonia and influenza mortality rate per 100 000 persons for states with vaccination laws and their synthetic counterfactuals.



Each state's synthetic counterfactual is constructed as a weighted average of all states without vaccination laws, in which the weights are determined by matching on the pneumonia and influenza mortality rate in each of the years before implementation of the state's law. Plots are presented in order of when the state laws were implemented, and implementation years for each state are in parentheses.

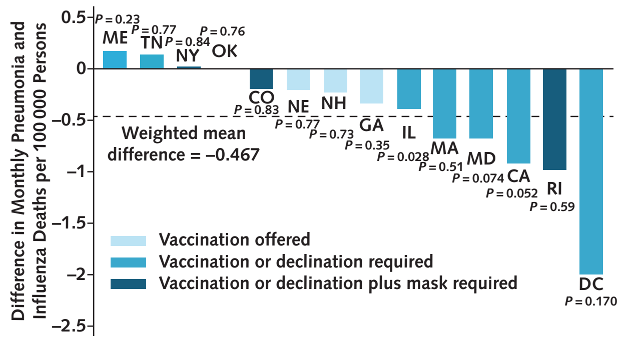
estimated change in the monthly log mortality rate into the monthly change in deaths per 100 000 persons, as we did with the synthetic control analysis. For efficiency, we weighted the analyses by the means of each state's population because the variance of mortality is inversely proportional to population.

We report 95% CIs based on SEs clustered at the state level to account for correlation within states over time, and we also report *P* values obtained from a nonparametric bootstrap procedure (section 4 of the **Supplement**) (24, 25).

The fixed-effects approach has its own limitations and assumptions. This approach assumes that, had the laws not been adopted, the log pneumonia and influenza mortality rates in adopting states would have followed the same trends as in the nonadopting states (the "parallel trends" assumption) (26) and that all states would share any changes caused by "common shocks" in any given year. Although these assumptions cannot be tested directly, we provide the following support for them. First, we estimated the trend difference between adopting and nonadopting states in the period before adoption (section 4.3 of the **Supplement**). Second, we allowed for potentially differential linear trends in the outcome variable across states by including state-specific linear time trends (27), and we included in our model several controls for observable state policies that might have affected influenza vaccination. Third, we examined whether the laws were associated with changes in mortality rates during peak influenza months for any nonpneumonia or noninfluenza causes of death, which could suggest the presence of unobserved confounding changes in hospital policies or quality of health care (28). We used the underlying cause-of-death code from the International Classification of Diseases, 10th Revision, to group these other deaths into 38 mutually exclusive categories, as defined by the National Vital Statistics System, and estimated our baseline regression for each category separately. *P* values in these models were corrected for multiple hypothesis testing (29). Fourth, we estimated whether the laws were associated with increases in adult, infant, and adolescent influenza or pneumococcal vaccination coverage (section 5 of the **Supplement**), which would be unexpected because hospital workers make up approximately 2% of the adult population (30, 31), and these laws should have no effect on infant and adolescent vaccination rates.

To examine how the average law's effect evolves over time, we estimated separate intervention effects for each of the first 3 years, the longest postadoption period we observed for every state that had an influenza law during our sample period. In addition, we estimated a model comparing the average effect in peak influenza months (December through March) and nonpeak months (April through November) to test whether effects were larger during peak influenza season. We also compared the effects for elderly (aged ≥65 years) versus nonelderly (aged 0 to 64 years) populations, because persons aged 65 years or older account for more than 85% of influenza-associated deaths (32), and we expected

Figure 3. Estimated difference in monthly pneumonia and influenza deaths per 100 000 persons between states with vaccination laws ("treated states") and their synthetic counterfactuals during the posttreatment period.



Bars represent estimates for each state compared with their synthetic controls for the average posttreatment difference in monthly pneumonia and influenza deaths per 100 000 persons. The *P* value corresponding to each estimate is constructed using the permutation-based method described by Abadie (22). To conduct inference, a statistic, *R*, is calculated for each of the treated state–year groups (for example, California's law was implemented in 2007–2008) and for a set of placebo state-years. There were 324 placebo effects estimated (1 for each of 36 donor states in each of the 9 years treatment was implemented). The *R* statistic represents the ratio of the posttreatment root mean squared prediction error (i.e., a measure of the effect size) to the pretreatment root mean squared prediction error (i.e., a measure of pretreatment goodness of fit). The reported *P* values for each treated state represent the percentage of placebo estimates with larger absolute *R* values than the corresponding estimate. The reported mean estimate represents an average of the treatment effect estimates weighted by state population.

the largest reductions in mortality in this group (section 4.4 of the **Supplement**).

We performed several sensitivity analyses to estimate the robustness of these results. We used an alternative "DIDm" estimator to evaluate whether our estimates from the fixed-effects approach were biased because of heterogeneity in the treatment effect over time or across states (section 4.2 of the **Supplement**) (33, 34). We repeated some of the analyses using a Poisson regression model (section 6 of the **Supplement**). We also repeated some of the analyses after dropping the H1N1 pandemic years, and separately after including 5 influenza years when the vaccine was poorly matched to circulating viruses. Finally, we calculated the E-value for our main estimate (35). The E-value measures the strength of the association between an unmeasured confounder and both the treatment and the outcome that would be required to explain our observed effect.

Role of the Funding Source

This study was not funded.

RESULTS

National Trends in Vaccination and Related Mortality

The proportion of U.S. hospital workers subject to an influenza vaccination law increased from less than 2% in 1995 to approximately 38% in 2017 (**Figure 1** [*left panel*]) as the number of states with a law increased from 1 (Alabama, which adopted a law before the start of our sample period) to 15 (including the District of Columbia). Figure 1 (*left panel*) plots this trend as well as self-reported influenza vaccination rates for U.S. adults employed in the hospital industry and those employed in all non–health care industries. Hospital worker influenza vaccination rates doubled from 43% in 1997–1998 to 87% in 2016–2017, increasing in tandem with the share of the hospital sector subject to a law. In contrast, vaccination rates among adults employed outside the health care industry increased by only 5 percentage points during the same period.

Trends in mortality rates are presented in Figure 1 (*right panel*), separately for states that did versus those that did not adopt a hospital worker influenza vaccination law. To give a sense of the timing of law adoption, we also show the share of the entire U.S. population that lived in states with vaccination laws in each influenza year. On average, states that adopted laws during this period had higher mortality at the start of the period than states that did not adopt laws; examination of individual state–level trends (not presented) shows that mortality trended downward for all states during these years, except for Alaska and Hawaii (both control states). Between the 1995–1996 and 2001–2002 influenza years, during which no states implemented laws, average mortality rates trended downward similarly in both groups of states. Consistent with this qualitative assessment of similar trends, results from a formal trend difference analysis (section 4.3 of the Supplement) show that we can rule out large differences in trends between states with and without vaccination laws during the years before adoption (difference in monthly change in mortality rate per 100 000 persons, 0.00015 [95% CI, −0.0016 to 0.0019]).

Similar trends continued until several large states adopted laws (12 states adopted laws between 2007–2008 and 2016–2017). Then, adopting states saw a larger decrease in mortality than nonadopting states. Supplement Figure 6 (available at Annals.org) shows that the timing of divergence in mortality trends closely coincides with the timing of law adoption.

Effects of Laws on Influenza-Related Mortality

Figure 2 shows the monthly mortality rate over time for each state with a vaccination law and its synthetic counterfactual, with the year of adoption denoted by a vertical black line. The estimated treatment effect for each state and its *P* value are presented in Figure 3. The point estimates from these analyses show that 10 of the 14 states with vaccination laws had greater reductions in pneumonia and influenza mortality after law adoption relative to their synthetic counterfactuals. However, we were able to reject the null hypothesis of no differential effect with a *P* value of 0.10 or less for only 3 states (Illinois, Maryland, and California). Each of these states require that the vaccine be offered to all hospital employees and require either vaccination or documentation of vaccine declination.

Estimation of the 2-way fixed-effects model showed that across all 14 states with vaccination laws, implementation of the law was associated with an average of 0.16 fewer pneumonia and influenza deaths per 100 000 persons each month (CI, −0.29 to −0.02; *P* = 0.022) (Table 1). Supplement Figure 3 (available at Annals.org) presents the estimated total reduction in the pneumonia and influenza mortality rate (*panel A*) and the estimated total reduction in pneumonia and influenza deaths (*panel B*) per influenza

Table 1. Change in Monthly Pneumonia and Influenza Deaths Associated With State Laws Regarding Hospital Worker Influenza Vaccination

Variable	Baseline Mean in Adopting States	Change in Monthly Pneumonia and Influenza Deaths per 100 000 Persons* (95% CI)	*P* Value
Average treatment effect†	6.4	−0.16 (−0.29 to −0.02)	0.022
Effect by years since adoption of law			
Year of adoption	–	−0.08 (−0.26 to 0.10)	0.37
First year after adoption	–	−0.17 (−0.32 to −0.01)	0.041
Second year after adoption	–	−0.20 (−0.38 to −0.02)	0.029
Third year after adoption	–	−0.34 (−0.54 to −0.13)	0.002
Effect by peak vs. nonpeak months‡			
Nonpeak months	5.6	−0.11 (−0.23 to 0.02)	0.099
Peak months	7.8	−0.29 (−0.47 to −0.12)	0.002
Effect by elderly vs. nonelderly§			
Age <65 y	1.1	−0.01 (−0.03 to 0.02)	0.66
Age ≥65 y	45.8	−1.19 (−2.09 to −0.26)	0.013

* Each estimate is interpreted as the change in the monthly pneumonia and influenza deaths per 100 000 persons that occurred in a state relative to what would be expected had the state not enacted the vaccination law. There were 9672 state–year–month observations in the sample.

† Details on methods are provided in section 4.1 of the Supplement (available at Annals.org). The dependent variable is the natural log of state pneumonia and influenza deaths per month per 100 000 persons. The raw regression coefficients represent the monthly change in logs (Supplement Table 2, available at Annals.org). The following equation was used to calculate the monthly change in the mortality rate in levels: [exp(monthly change in logs) − 1] × [baseline mean]. The bootstrapped CIs and *P* values are reported in Supplement Table 2.

‡ Peak months are December through March, and nonpeak months are April through November.

§ Changes in age-specific mortality rates, calculated using age-specific populations. Details on estimation methods for the heterogeneous effects are provided in section 4.4 of the Supplement, and tests for the differences between each group are shown in Supplement Table 2.

Table 2. Sensitivity Analyses for Estimates of Hospital Worker Influenza Vaccination Laws on the Pneumonia and Influenza Mortality Rate per 100 000 Persons

Sensitivity Analysis	Change in Monthly Pneumonia and Influenza Deaths per 100 000 Persons* (95% CI)	*P* Value
Linear trends and covariates excluded		
Covariates and state-specific trends excluded†	–0.429 (–0.766 to –0.073)	0.020
State-specific trends excluded	–0.443 (–0.699 to –0.174)	0.002
Covariates excluded	–0.192 (–0.346 to –0.033)	0.019
Different years included		
Years with <50% match between vaccine and circulating strains included‡	–0.117 (–0.287 to 0.057)	0.180
H1N1 influenza years (2008–2009 and 2009–2010) excluded	–0.342 (–0.596 to –0.076)	0.013
Log linear (Poisson) model estimation§	–0.202 (–0.328 to –0.074)	0.002
Annual data‖		
Fixed effects for year estimator	–0.185 (–0.322 to –0.044)	0.012
Multiple period ("DIDm") estimator	–0.368 (–0.593 to –0.133)	0.003

* Each estimate is interpreted as the change in the monthly pneumonia and influenza death rate per 100 000 persons that occurred in a state relative to what would be expected had the state not enacted the vaccination law.
† Covariates refer to state-level, time-varying controls for laws regarding vaccination in long-term care facilities and laws regarding vaccination in childcare facilities.
‡ See Supplement Figure 5 (available at Annals.org) for match rates by influenza year.
§ In the Poisson model, the outcome was the number of deaths rather than the log mortality rate. The reported coefficients from the Poisson specification similarly represent the change in monthly deaths per 100 000 persons, calculated as [exp(monthly change in logs) − 1] × [baseline mean]. The baseline mean is the overall average reported in Table 1 (6.4 deaths per 100 000 persons).
‖ Although the main specification used monthly data (to explore differences in the effects across months), we also aggregated the data to the annual (influenza year) level. The estimator here is identical to the primary model except that it is estimated at the annual level and includes year fixed effects in place of year–month fixed effects. The "multiple period" follows the "DIDm" estimator of de Chaisemartin and d'Haultfoeuille (34) and was implemented using the did_multiplegt package in Stata. Because of the large number of time periods in the monthly data, the multiple period estimator could only be estimated using annual data. The multiple period estimator requires specifying the number of posttreatment periods the treatment effect is averaged over, and we averaged over the first 4 years after treatment because that is the maximum number of posttreatment years available for all 14 states with vaccination laws.

year that resulted from law implementation. For example, during the 2016–2017 influenza year, all of the ever-adopting states had implemented their laws, and 1822 deaths were averted because of the laws (CI, 275 to 3337 deaths).

Additional Results

Vaccination laws led to a sustained decrease in the pneumonia and influenza mortality rate in years 1, 2, and 3 after adoption (Table 1). Although the average effects increased each year, the effects were not significantly different. The estimated effect of the laws on all-age mortality was larger during peak compared with nonpeak influenza months (−0.29 vs. −0.11 deaths per 100 000 persons; $P < 0.017$ for the difference [Supplement Table 2, available at Annals.org]). Mortality reductions are driven by decreases among elderly (aged ≥65 years) compared with nonelderly persons: The laws resulted in 1.19 fewer pneumonia and influenza deaths per 100 000 elderly persons (CI, −2.09 to −0.26) versus 0.01 fewer deaths per 100 000 nonelderly persons (CI, −0.03 to 0.02). Supplement Table 7 (available at Annals.org) shows that of all categories for cause of death that we studied, only death caused by pneumonia and influenza was associated with state law implementation (Bonferroni-corrected P = 0.023). As shown in Supplement Tables 3 and 4 (available at Annals.org), we found no evidence that the laws were associated with changes in influenza or pneumococcal vaccination coverage among the general adult population or with changes in vaccination among adolescents and infants.

Table 2 reports the results of the sensitivity analyses. When state-specific time trends or covariates were excluded from the model, the estimated association between the laws and pneumonia and influenza mortality was larger. In addition, the estimated association was larger when we excluded H1N1 influenza years and smaller when the sample was expanded to include years in which the vaccine was poorly matched to the circulating strains. All of these results align with our expectations. Table 2 also shows that the reduction in the pneumonia and influenza mortality rate was similar when estimated with a Poisson regression model, which increases confidence in the original model, and presents the results for the DIDm estimator, which are consistent with our main findings. Supplement Table 5 (available at Annals.org) presents our calculated E-values, which range from 1.39 to 3.4 and support the robustness of our findings.

DISCUSSION

Our analysis of state-level, longitudinal data found that state laws that promote influenza vaccination for hospital workers were associated with reductions in pneumonia and influenza mortality in the general population during years when the vaccine was a good match for the circulating strains of influenza. Our estimates suggest that adoption of a law reduced annual pneumonia and influenza mortality by an average of 1.92 deaths per 100 000 persons, or 2.5% in relative terms, with these reductions primarily occurring among elderly persons and during the months of peak influenza circulation.

The magnitude of this reduction is modest relative to estimates from other studies. For example, several cluster randomized controlled trials conducted in long-term care facilities found that increased influenza vaccination of health care workers decreased all-cause mortality by approximately 30% to 40% (36–38). These studies, however, have been criticized for showing implausibly large estimated effects on all-cause mortality in the absence of effects on more specific outcomes (9, 10). Our estimates are more in line with a recent study that found that vaccination mandates for health care workers in California were associated with an approximate 20% decrease in inpatient diagnoses of influenza (11).

Our finding that the pneumonia and influenza mortality reductions were concentrated among elderly persons aligns with broader literature on the effects of influenza vaccination (39–43). Because elderly persons are sometimes less responsive to the vaccine than other age groups (44), this result demonstrates that vaccinating hospital workers might be an effective strategy for protecting this vulnerable population from influenza.

The synthetic control analysis we used to assess the effect of individual state laws on mortality from pneumonia and influenza yields more precisely estimated effects in larger states, and we urge caution when comparing the effect sizes across states and thus across different types of laws because we cannot statistically differentiate them from one another. Nevertheless, it is notable that all 3 states with statistically significant reductions (Illinois, Maryland, and California), as well as all 5 states with estimated reductions surpassing the mean, had relatively stringent laws that required more than simply offering the vaccine to employees. The states with strong laws but little or no estimated reduction in mortality are primarily small states with less precise estimates (Maine and Oklahoma) or the last of the states to implement their laws (Colorado and New York). These results, when considered together, suggest that laws mandating hospital worker vaccination may have a greater effect on pneumonia and influenza mortality than laws that only require hospitals to offer vaccination. This is consistent with prior studies suggesting that law strength is associated with hospital workers' vaccination coverage (8).

This study has additional limitations. First, our focus on large-scale national data precluded us from analyzing more specific outcomes, such as laboratory-confirmed or hospital-acquired influenza. Cause-of-death data can be inaccurate, and influenza is underreported on death certificates, raising the possibility of measurement error in our outcome variable. Second, we lacked data on influenza vaccination requirements implemented independently by hospitals, which increased during the years studied (45). If these policies appeared more often in states without state laws, our results understate the mortality effects of these laws. On the other hand, if hospitals were more likely to require workers to be vaccinated after states passed laws, spurring change in hospital policies may be an important pathway through which the laws reduced pneumonia and influenza mortality. Third, although the average effect of the law seemed to grow during the first 3 years after adoption, our study lacked the statistical power to confirm these dynamics.

Finally, our analyses relied on the assumption that there were no unobserved confounders associated with the passage of these state laws that would have affected mortality. Consistent with this assumption, we found no evidence that adult, infant, or adolescent influenza or pneumococcal vaccination coverage increased differentially in adopting versus nonadopting states. We also found no evidence that adoption of the laws coincided with broader mortality improvements in adopting states, which could indicate confounding changes in the quality of hospitals, providers, or medical care in general. Finally, we also note that nationwide changes, such as new CDC recommendations for vaccinating young children against influenza, would affect control states as well as states with vaccination laws.

In conclusion, our research suggests that state laws promoting hospital worker vaccination against influenza can be effective in preventing deaths from pneumonia and influenza, particularly among elderly persons. Overall, our findings are consistent with the idea that vaccinating hospital workers reduces the spread of influenza and, by doing so, protects the lives of more vulnerable populations.

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Reproducible Research Statement: *Study protocol:* Not available. *Statistical code:* Available at https://github.com/cdwhite1/HCW-Vaccination-Project. *Data set:* Access to mortality data is restricted but can be obtained through application from the National Vital Statistics System (National Center for Health Statistics, CDC). All other data sources are publicly available.

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