Legislating Longevity: State Public Health Laws and Mortality in the Early Twentieth Century*

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December 8, 2025

Abstract

State legislatures enacted numerous public-health laws during the twentieth century, most of which likely had negligible effects on mortality. Using data on the universe of state-level public-health laws and regulations, I test whether these laws, taken together, account for a meaningful decline in mortality. To address endogeneity, I instrument for public-health legislation using the legislative calendar, session length, and legislator salaries. Both OLS and IV estimates indicate that public-health laws reduced mortality, whereas other laws or repeals of public-health laws did not. Legislatures were particularly effective at reducing deaths from tuberculosis, influenza/pneumonia, and childhood diarrhea. Additionally, more-prolific legislatures passed more effective laws. A text analysis of the laws shows that housing/tenement and drug-safety laws are most associated with falling mortality. The universe of public-health laws can account for approximately two-thirds of the mortality decline during the study period.

JEL codes: I18, N32, K32, H75
Keywords: text analysis, topic modeling, Latent Dirichlet Allocation, public health, public health laws, mortality transition, vital statistics, state legislators, legislative schedules, drug safety, tenements

*I am grateful for feedback from Mark Anderson, Wesley Hector Blanco, Blundell, Patrick Carlin, Alan Dye, Daniel Maggio, Felix Munoz-Garcia, Anne Piehl, David Rosenkranz, Chris Stoddard, Carly Urban, and seminar participants at Columbia University, Fordham University, Montana State Univeresity, Rutgers University, and Washington State University. All errors are my own.

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1 Introduction

One of the most remarkable trends since the Industrial Revolution is the rise in life expectancy. At the founding of the United States, one in five children did not survive infancy, and life expectancy at birth was likely just over 40 years (Costa, 2015). Those who survived childhood fared better but still died at ages that would be considered premature by modern standards. Life expectancy at age 10 was roughly 55 years. Perhaps surprisingly, this transition did not begin with the Industrial Revolution. Life expectancy fell during much of the 1800s, and life expectancy at age 10 in 1900 was only 50 years. It was not until the 1880s, around the time germ theory gained acceptance among leading scientists, that mortality began to decline. Over the next hundred years, life expectancy at birth would nearly double, with most of the increase occurring from 1880 to 1930. But germ theory alone could not have caused the mortality transition, any more than calculus alone could have put a man on the moon. Just as steel had to be cut and jet fuel burned, public-health officials and residents had to reorganize daily life to avoid pathogens.

Despite being one of the most important questions in economic and demographic history, remarkably little is known about which actions, private or public, caused the mortality transition. Numerous studies document that specific public-health interventions reduced mortality from particular causes, prominent examples including clean water and sewer systems for typhoid fever (Anderson et al., 2022; Alsan and Goldin, 2019; Beach et al., 2016; Ferrie and Troesken, 2008; Troesken, 2004) and vaccination campaigns for smallpox (Troesken, 2019; Brehm and Saavedra, 2025). However, even the provision of filtered water through municipal waterworks accounts for only a small fraction of the decline in infant mortality, and an even smaller fraction of the decline in overall mortality (Anderson et al., 2022). While many mechanisms such as rising incomes, improved nutrition, and sanitation have been proposed, no well-identified study using modern applied microeconomic methods has yet accounted for this major societal change.

One explanation is that the mortality transition did not have a single cause, nor even a handful of causes. Once germ theory established that pathogens spread disease, daily life had

to be reorganized in numerous ways, from the obvious, such as drinking clean water, properly disposing of waste, and quarantining, to the more mundane, such as banning public spitting or regulating the disposal of dead livestock.

Measuring these changes presents several challenges. First, many were likely implemented simultaneously. Even for a single intervention such as quarantine laws, there may have been numerous small tweaks, yielding no clear implementation date. This paper embraces a polycausal explanation of the mortality transition without abandoning hoping for modern causal identification.

I digitize the universe of state-level public-health laws and regulations enacted between June 1911 and December 1928 from annual reports published by the United States Public Health Service (USPHS). These reports catalog laws the USPHS classified as public-health measures, ranging from funding for waterworks and vaccination mandates to bans on spitting on trains and regulations on the sale of horsehair brushes. I then merge these data with monthly all-cause mortality and annual cause-of-death rates from the vital statistics.

Many public-health laws are likely responses to disease outbreaks rather than causes of mortality declines. To address this endogeneity, I instrument for the passage of public-health laws using the legislative calendar and session limits, which are set years in advance, often by state constitutions. Because most public-health laws are enacted during regular sessions, which are predictable well before any outbreak, states that meet in even years versus odd years experience mechanically different enactment timing: after one session, the even-year state will have a new wave of public-health laws that the odd-year state will not adopt until roughly twelve months later. In addition to baseline two-way fixed-effects and instrumental-variables estimates, I also implement local projection differences.

Lastly, I use text analysis (both dictionary methods and topic modeling) to describe the public-health laws enacted during the period and to estimate which types of laws are most associated with mortality declines. The unsupervised model identifies topics corresponding to well-studied areas, such as communicable disease and water/sewer systems, as well as less-studied areas, such as tenements and drug safety.

I find that a single public-health law reduced mortality on average by 5 to 8% of one percent (0.0005–0.0008 log points). These estimates are not driven by public-health laws that repeal prior laws, by non–public-health laws passed contemporaneously, and by Prohibition or women's suffrage. Legislatures that were more prolific (i.e., passed more laws during the period) were also more effective: each public-health law they enacted reduced mortality by a larger amount. After correcting for multiple-hypothesis testing, drug-safety laws and laws regarding the collection of vital statistics are most associated with mortality declines. Public-health laws had the largest effects on influenza, pneumonia, childhood diarrhea, tuberculosis, and infant mortality. Taken together, these laws can account for almost two-thirds of the mortality decline during the period.

This paper contributes to several strands of literature. First, it contributes to work explaining falling mortality rates in the early twentieth century (Preston and Haines, 2014). Many explanations have been advanced for this trend including water/sewer systems (Anderson et al., 2022; Alsan and Goldin, 2019; Troesken, 2004), vaccinations (Troesken, 2019), income/nutrition (Floud et al., 2011), and health-care infrastructure (Hollingsworth et al., 2024). However, any intervention considered in isolation, while perhaps highly effective for certain diseases, leaves most of the mortality decline unexplained. Second, this paper contributes to the literature on the effectiveness of nonpharmaceutical interventions and the 1918 influenza pandemic (Beach et al., 2022; Hatchett et al., 2007). I find that influenza/pneumonia was an area in which public-health laws were particularly effective, and my sample includes the 1918 influenza wave and all subsequent waves, whereas most prior research focuses only on the fall 1918 wave. Third, I contribute to the literature on the role of laws and institutions in the transition to a modern economy (Acemoglu et al., 2001, 2005; Acemoglu and Johnson, 2007; Matsuura, 2015). I find that any single law has a trivial effect on mortality, even when statistically significant. Thus, what was needed was not a single law but a system of laws, or an institution of public health.

2 Background

2.1 Germ Theory of Disease

2.2 State Boards of Health

2.3 State Health Interventions

The provision of filtered water—often cited as one of the most effective public health interventions—can explain only a small fraction of the overall mortality decline. Several well-identified studies show that filtered water saves lives, particularly among infants. For example, Anderson et al. (2022), Beach et al. (2016), and Cutler and Miller (2005) find that water filtration reduces deaths from typhoid fever by approximately 20%.[1] Infants appear to particularly benefit from clean-water interventions, with estimates frequently indicating a 10–15% reduction in infant mortality (Anderson et al., 2022; Alsan and Goldin, 2019; Anderson et al., 2021).[2] However, even water interventions cannot explain most of the mortality decline. Anderson et al. (2021) find that, although clean water reduces deaths from waterborne causes and total infant deaths, filtration and chlorination together can explain only 1–2% of the total mortality decline.

- Tuberculosis
- Vaccination
- Food and dairy
- Modern medicine: hospitals, physician licenses, and drugs

[1] This result is so consistent that typhoid fever death rates are often used as a proxy for water quality. See Ferrie and Troesken (2008) and Beach et al. (2016).

[2] A frequently cited estimate that clean water accounts for half the infant mortality decline comes from Cutler and Miller (2005). Anderson et al. (2021) show smaller effects after correcting digitization errors, using population denominators, revising intervention dates, and adding additional cities.

2.4 Legislative schedules and state constitutions

3 Data

The law data come from an annual report published by the U.S. Public Health Service between June 1911 and December 1928, titled *State Laws and Regulations Pertaining to Public Health.* Each report lists all state-level public health laws passed that year, covering topics ranging from mandatory quarantines to the disposal of dead livestock. Appendix Figure A.1 provides examples of two such laws. During this period, 5,867 state-level public health laws were enacted. I digitize the titles and dates of each law by hand and obtain the full text through optical character recognition (OCR).[3]

Kimball (1922) reports data on the frequency of regularly scheduled legislative sessions, limits on session length, and legislator salaries. State legislatures met annually, biennially, or quadrennially. Some states limited sessions to 50 days or fewer, while others imposed longer limits or no limit at all. I top-code states without session limits at 180 days, as there is a sharp decline in the passage of public health laws roughly six months after the start of regular sessions. Legislators were paid either on a fixed basis (e.g., annually) or per day in session. To normalize wages, I calculate "potential salary" as either the annual salary (if legislators were paid annually) or the salary a legislator would have earned had the session reached its limit without special sessions.

By combining the frequency of legislative sessions with the last date of a regular session before the sample begins (pre-1911 sessions), I estimate how many months a legislature would have been expected to meet since June 1911.[4] I code all states as starting with zero cumulative sessions. In the month when the legislature is expected to meet, cumulative sessions increase by one. In the following month, cumulative sessions increase again if the session length is at least 30 days, and in the next month only if the session length is at least 60 days, and

[3]To obtain the OCR text for law n, I identify the page on which law n begins (p_n) and the page of law $n+1$ (p_{n+1}). The text of law n must lie within the interval $[p_n, p_{n+1}]$, but may also contain material from laws $n-1$ and $n+1$. I start by searching for the title of law n and truncate any text preceding it. I then search for the title of law $n+1$ and truncate any text after it, including the title itself. I am able to locate both titles 79% of the time.

[4]The historical legislative sessions are from Babbitt (1912).

so forth. For sessions without a limit, this process continues until the cumulative number of expected sessions increases by six (since session length is top-coded at 180 days). This methodology allows me to generate the expected number of months a state legislature is in session using data available from before the sample period, ensuring that it cannot be endogenous to mortality shocks such as the 1918 influenza pandemic.

I begin by generating cumulative counts of the number of laws passed in state s by month t since June 1911. Formally, let the number of public health laws passed in state s in month t be $Laws_{s,t}$. Then the cumulative number of laws is $cLaws_{s,t} = \sum_{\tau=t_0}^{t} Laws_{s,\tau}$.

The mortality rate comes from the annual report of vital statistics. I construct it by dividing monthly death counts by population estimates obtained through linear interpolation between the 1910, 1920, and 1930 censuses. Mortality statistics become available for a state only once it enters the "registration area," meaning that the Bureau of the Census deems the data sufficiently reliable. For this reason, the panel is unbalanced; however, cumulative laws are always measured starting in June 1911. Cause-of-death data are sparse at the monthly level. I therefore supplement the analysis with annual mortality data, using a simple average of the cumulative monthly law counts in that year.

I use two natural language processing techniques to analyze the text of the laws. First, I apply simple dictionary methods, searching the full text for substrings that identify laws containing either a clear punishment or a repeal of a prior law. To identify punishments, I search for the substrings "fine," "jail," "prison," or "punish." I classify a law as repealing an existing law if it contains the substrings "repeal," "rescind," or "nullif." Second, I use Latent Dirichlet Allocation (LDA), an unsupervised machine learning method, to assign each law to topics. I discuss LDA in detail in Section 6.

Summary statistics are presented in Table 1. The mean monthly mortality rate is 105 deaths per 100,000. In the average month, a state passes 0.7 public health laws, but the distribution is skewed, with many laws enacted during legislative sessions (up to 41 in a single month). The cumulative number of laws passed in a state-month cell is 73, of which 15 are repeals of existing laws and 25 contain an explicit punishment. The average state-month

Table 1: Summary statistics

	Mean	S.D.	Min	Max	N
Monthly mortality rate	105.5	30.2	46.9	636.5	6,850
Laws passed that month	0.7	2.3	0.0	41.0	6,850
Word count	965.0	3745.6	0.0	71919.0	6,850
Repeal laws	0.1	0.7	0.0	13.0	6,850
Laws with punishments	0.2	0.9	0.0	16.0	6,850
Cumulative laws	73.1	62.1	0.0	422.0	6,850
Cumulative word count	104.9	90.8	0.0	636.1	6,850
Cumulative repeal laws	14.6	13.9	0.0	70.0	6,850
Cumulative laws with punishments	24.6	19.5	0.0	113.0	6,850
Year	1920.8	4.9	1911.0	1928.0	6,850
Month	6.6	3.4	1.0	12.0	6,850
Salary	3.8	3.2	0.5	15.0	6,850
Session length	111.8	57.6	40.0	180.0	6,850
In session	0.2	0.4	0.0	1.0	6,850
Cumulative months in sessions	22.8	19.0	0.0	102.0	6,850

Notes: Each observation is a state-month cell. Mortality data come from the Vital Statistics. Public health laws are restricted to laws passed between June 1911 and December 1928. Salary is annual salary measured in hundreds of 1919 dollars. Session length is the maximum length of regular sessions, top coded at 180 for states with no limit, and is measured in days.

cell includes over 100,000 words of public health laws passed by the legislature. Since the beginning of the sample, state legislators were expected to have been in regular session for an average of 22 months. Annual salaries for state legislators averaged $350 (in 1919 dollars), and session lengths averaged 111 days.

4 Methodology

Estimating the effects of public health laws poses several challenges. First, the cumulative number of laws is nearly continuous, taking on 285 distinct values. Second, the number of laws changes frequently within a state: the median state-month passes 14 laws over the prior 24 months, the 95th percentile passes 42, and the 5th percentile passes 3. Third, the effects of public health laws may be dynamic, with new laws enacted before the effects of earlier laws stabilize. Fourth, public health laws are likely endogenous, as lawmakers may respond to public health crises such as the 1918 influenza pandemic or outbreaks of smallpox or polio.

To address these challenges, I consider three identification strategies, each involving trade-offs between statistical power and the strength of assumptions.

4.1 Baseline: Two-Way Fixed Effects

As a baseline, I estimate a two-way fixed effects (TWFE) specification:

$$\ln(m_{st}) = \alpha_t + \beta_s + \delta\, cLaws_{st} + \epsilon_{st}, \tag{1}$$

where m_{st} is the monthly mortality rate in state s at time t, α_t and β_s are time and state fixed effects, respectively, and $cLaws_{st}$ is either the cumulative number of public health laws or the cumulative number of laws within a given topic.

The two-way fixed effects model has the advantage of being well powered and controls for factors that are relatively fixed at the state level, such as climate, endemic disease environments, and population density. Time fixed effects account for trends in general knowledge about germ theory, medical innovations, and national events such as the 1918 influenza pandemic, World War I, or recessions. Because instruments are not required, I can also estimate variants of the two-way fixed effects model that replace the cumulative number of laws with the number of laws in a given topic or restrict the sample to laws with specific text features.

The baseline model also has several weaknesses. Most notably, cumulative public health laws are likely endogenous to public health shocks. A prominent example is health boards passing regulations during the 1918 influenza pandemic, though responses to outbreaks of other diseases—especially smallpox—were also common. The laws are heterogeneous in nature, implying that the two-way fixed effects estimator may be biased (Goodman-Bacon, 2021; De Chaisemartin and D'haultfœuille, 2023; Callaway and Sant'Anna, 2021). Lastly, the baseline model assumes that the effects of public health laws are static: they are implemented without delay and their effectiveness is constant over time. To address these limitations, beginning with endogeneity, I consider two additional estimation strategies.

4.2 Instrumental variables strategy

Public health laws and regulations arose in three ways. First, a health board could issue a regulation under the powers granted by the state legislature. These regulations are the most likely to be endogenous, as they were often enacted in response to disease outbreaks. Second, state legislatures could pass laws during extraordinary sessions, generally convened by the governor and often prompted by new information. Lastly, state legislatures met at regular intervals defined in their state constitutions. Most commonly, they convened in January, with sessions lasting several months subject to constitutional limits. Some legislatures held regular sessions in odd years, others only in even years, while some met annually; one state (Alabama) met quadrennially.

Most public health laws were passed during regular sessions. Figure 1 illustrates the number of laws passed by year for states with different legislative schedules. States that met annually (top left panel) passed a steady stream of laws, with no clear pattern favoring odd or even years. States that met biennially beginning in 1913 passed most of their laws in odd years. Some new laws were still enacted in even years—presumably through health board regulations or special sessions—but at a much lower rate. A similar pattern favoring even years appears for states that began meeting biennially in even years starting in 1912. Alabama, with a quadrennial schedule, shows a sharp wave of laws passed every fourth year.

States with longer session limits also passed more laws. Figure 2 shows the number of laws passed by month for states that convened in January during years with scheduled regular sessions. Few laws were enacted in January, suggesting that legislatures convened closer to the end of the month or that public health laws were not the first legislative priority. States meeting for 40–60 days passed relatively few laws, with legislative activity peaking in March. States with limits of 70 to 150 days reached a higher peak and continued passing laws through at least May, whereas states without limits passed the most laws overall and continued doing so until July. The final panel shows the same states during years without a scheduled regular session. In those years, there is no January peak, confirming that these patterns are not driven by seasonality in health board regulatory activity.

Figure 1: Laws passed by session schedule

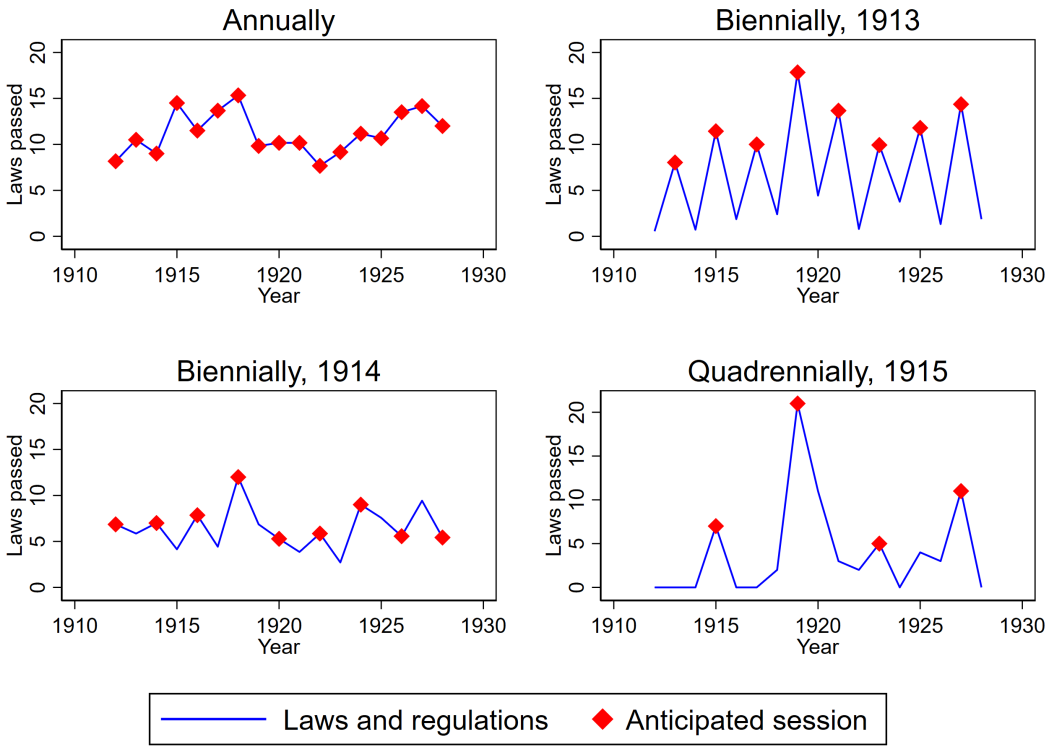
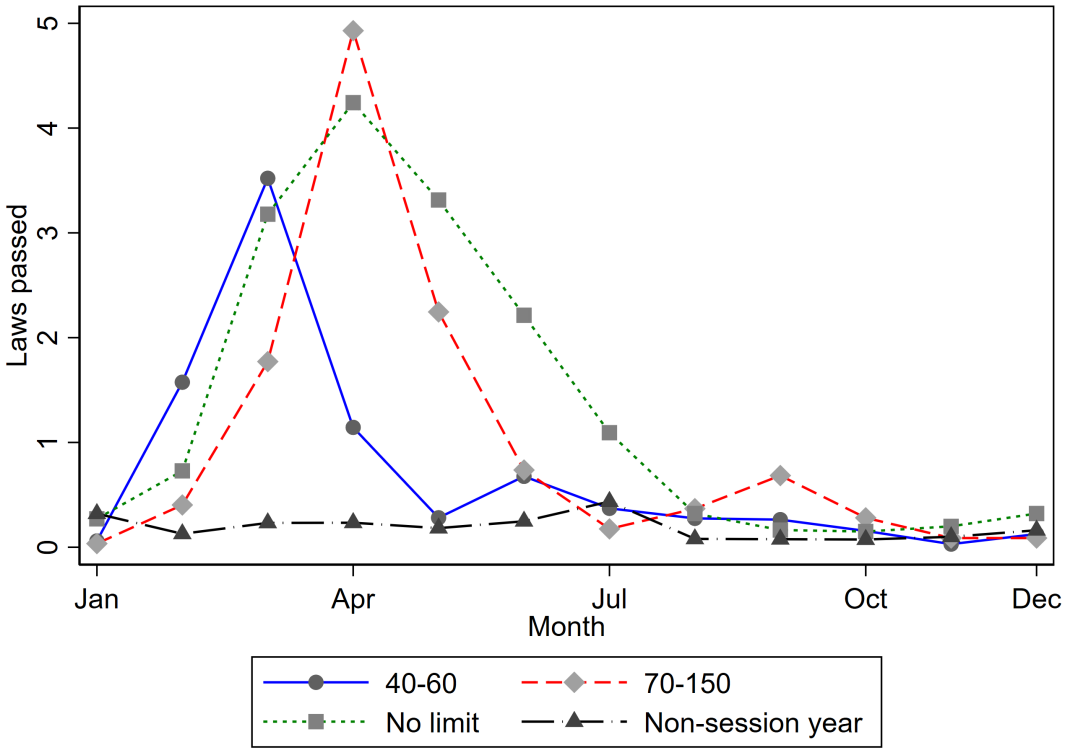


Figure 2: Laws passed by month and session limit



Notes: Includes states with sessions starting January.

These empirical regularities motivate an instrumental variables strategy. Specifically, I instrument for the cumulative number of public health laws using the cumulative number of months the legislature has been in regular session. I also interact this instrument with the annual salary of state legislators. Because regular sessions are predictable—often decades in advance—without any knowledge of future mortality shocks, the instruments are likely to satisfy the exclusion restriction. Moreover, the fact that legislative schedules clearly predict the passage of public health laws ensures that the IV relevance condition holds.

To illustrate how the legislative schedule aids identification, consider the following example. Suppose there are only two states, A and B. In both states, the legislatures meet biennially and enact ten public health laws each time they convene. Further assume both states have the same number of public health laws in June 1911. The states have identical legal institutions, except the legislative schedule: state A's legislature meets in January of even years whereas state B's meets in January of odd years. In 1912, state A will have ten more public health laws than state B; in 1913, state B enacts ten laws and catches up. In 1914, state A enacts ten additional laws, which state B again matches in 1915. This pattern continues: in even years, state A will have ten more laws than state B, and in odd years the two states will have the same number of laws. Thus, if state A has lower mortality than state B in even years and similar mortality in odd years, that pattern would indicate that contemporaneous public health laws affect mortality. For the instrument to be endogenous, an unobserved mortality shock would have to follow the same biennial schedule, which is inconsistent with secular trends such as rising income, nutrition, or sanitation (unless those variables were themselves direct outcomes of legislative activity).

I estimate the following first-stage regression:

$$\text{Laws}_{st} = \gamma_s + \lambda_t + \pi_1 \,\text{SessionMonths}_{st} + \pi_2 \,(\text{SessionMonths}_{st} \times \text{Salary}_s) + \nu_{st}, \qquad (2)$$

where $\text{SessionMonths}_{st}$ is the cumulative number of months that the legislature in state s has been in regular session from the beginning of the sample to time t, and Salary_s is the annual

salary of legislators in state s.[5]

The IV estimator is not without its trade-offs. IV estimates result in a loss of power relative to the two-way fixed effects estimator. In addition, treatment effects are still assumed to be static rather than varying over event time. I relax this latter assumption with the final estimator.

4.3 Event Study Estimation

The challenge of estimating an event-study design in this context is that treatment is continuous and changes from period to period. Most modern difference-in-differences methods consider the binary, single-treatment case, and generalizations typically extend to either continuous treatment or time-varying treatment, but not both. One exception is the local projection difference-in-differences (LP-DiD) approach developed by Dube et al. (2023).

To implement such an event study, I assume that the effects of previously passed laws stabilize after a certain number of months. This allows dynamic treatment effects around the passage of a law. The treatment effect for each event time can then be estimated by restricting the sample to two groups. The treatment group includes observations in which no laws were passed in the months leading up to a new law (so that prior effects have stabilized) and no additional laws are passed until the effects of the new law have stabilized. The control group consists of "clean controls," defined as observations in which no laws were passed during the event-window horizon (either before or after). Because very few states go more than a year and a half without passing public health laws, I require that treatment effects stabilize after five months.

Formally, for each event time h, I estimate:

$$\begin{aligned} \ln(m_{s,t+h}) - \ln(m_{s,t}) &= \beta^h \, \Delta Laws_{s,t} + \delta_t^h \\ &\quad + \gamma_1^h \ln(m_{s,t-1}) + \gamma_2^h \ln(m_{s,t-2}) + e_{st}^h, \end{aligned}$$

[5]The variable $\text{SessionMonths}_{st}$ assumes that regular sessions meet for their constitutional limit, and that legislatures without limits meet for 180 days. The early conclusion of a session could reflect a response to a disease outbreak.

using the set of observations for which both $Laws_{s,t} = Laws_{s,t+h}$ and $Laws_{s,t-1} = Laws_{s,t-5}$ (the treatment group), or $Laws_{s,t+h} = Laws_{s,t-5}$ (the "clean" controls). This method permits heterogeneous treatment effects and allows for five months of dynamic effects before stabilization.

For all three methods, I cluster standard errors at the state level. I also conduct several robustness checks, such as controlling for the occupational, racial, and age distributions of states (interpolated linearly between census years), including region-specific linear trends, restricting the sample to laws that are not repeals, and controlling for other types of laws.

5 Results

The main results appear in Table 2. The two-way fixed effects estimates in Panel A suggest that each law passed reduces mortality by between 0.03% and 0.06% (three to six percent of one percent). Although each individual law has only a trivial effect on mortality, the cumulative impact of hundreds of such laws (as many states enacted during this period) amounts to a meaningful reduction. The baseline result in column 1 is robust to restricting to a balanced panel of states (column 2), controlling for lagged mortality (column 3), and omitting population weights for each month-state cell (column 4).

Instrumenting for public health laws with the legislative schedule increases the magnitude of the estimates (Panel B). In this case, a single law reduces mortality by between 0.05% and 0.07% (five to seven percent of one percent). The larger estimates are consistent with legislatures passing public health laws in response to infectious disease outbreaks. In such cases, mortality may rise when laws are enacted, but the causal chain runs in reverse, motivating the use of a valid IV approach. The first stage (Panel C) shows that the cumulative number of months a legislature is in session predicts more public health laws. Although the stand-alone coefficient is statistically significant in only one specification, the interaction of legislative months with legislative salary is positive and significant across all specifications. For example, in the baseline specification, legislatures with an annual salary of $1,000 passed approximately 0.68 public health laws per month, while increasing salary by an additional

Table 2: OLS estimates of the effect of public health laws

	(1)	(2)	(3)	(4)
	Panel A: OLS			
Cumulative laws	-0.000568***	-0.000535***	-0.000313***	-0.000535**
	(0.0000917)	(0.000107)	(0.0000495)	(0.000215)
	Panel B: Second stage			
Cumulative laws	-0.000713***	-0.000721***	-0.000746***	-0.000535**
	(0.000121)	(0.000149)	(0.000180)	(0.000215)
	Panel C: First stage			
Cumulative months in sessions	0.501	0.882**	0.493	0.026
	(0.488)	(0.422)	(0.491)	(0.564)
Cumulative sessions × salary	0.176***	0.154***	0.177***	0.222***
	(0.026)	(0.021)	(0.026)	(0.041)
F-stat of IVs	361.41	232.69	419.78	71.71
N	6,850	4,642	6,805	6,850
Balanced	N	Y	N	N
Lagged mortality	N	N	Y	N
Weighted	Y	Y	Y	N

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p*** < 0.01$.

$1,000 raised the rate to 0.85 per month. The F-statistics on the instruments range from 71 to 361.[6]

The results are driven by public health laws that did not repeal existing statutes. Table 3 presents results based on a classification of laws using dictionary methods. Column 1 reports results excluding repeal tokens from the law text. The effect size increases relative to the OLS estimates, reaching approximately seven percent of one percent. Column 2 reports the specification restricted to repeal laws, which yields a negative and significant coefficient; however, this result appears to be driven by the fact that repeals tend to occur while legislatures are in session and passing other public health laws. Column 3 includes both non-repeal and repeal laws. The effect of non-repeal laws is significant and twenty-four times larger in magnitude than that of repeal laws. The finding that repeals do not increase mortality is consistent with legislatures repealing laws after outbreaks have subsided. For example, if smallpox had

[6]Using only the cumulative number of sessions as an IV produces similar estimates.

Table 3: Effects of laws classified by dictionary methods

	(1)	(2)	(3)	(4)
Cumulative non-repeal laws	-0.000668***		-0.000664***	
	(0.000101)		(0.000133)	
Cumulative repeal laws		-0.00183*	-0.0000271	
		(0.000912)	(0.000707)	
Cumulative laws with punishments				-0.000842
				(0.000922)

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p***< 0.01$.

Table 4: Measuring laws by word count

	(1)	(2)
Cumulative word count	-0.000347***	0.0000374
	(0.0000873)	(0.000186)
Prolificness × word count		-0.000491**
		(0.000195)

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p***< 0.01$.

already disappeared from a state, repealing a vaccination mandate would be unlikely to affect mortality. Column 4 considers laws containing punishment tokens. The estimated effects are similar in size but statistically insignificant.

An alternative to counting laws is to count the number of words in enacted laws. This measure accounts for the possibility that some states combine provisions that would constitute several separate laws elsewhere into a single statute. Table 4 replaces the cumulative number of laws with the cumulative number of words in those laws (measured in thousands). An additional 1,000 words of public-health legislation is associated with a decline in mortality of approximately 0.035%.

More prolific legislatures were also more effective. I measure prolificness as the total number of laws passed over the sample period, rescaled to the unit interval:

$$\text{Prolificness}_s = \frac{cLaws_{s,\text{Dec 1928}} - \min_{s'}\left(cLaws_{s',\text{Dec 1928}}\right)}{\max_{s'}\left(cLaws_{s',\text{Dec 1928}}\right) - \min_{s'}\left(cLaws_{s',\text{Dec 1928}}\right)}. \tag{3}$$

The interaction of prolificness with cumulative word count is negative, indicating that for the most prolific legislatures (Prolificness = 1) an additional 1,000 words of public-health

legislation corresponds to a 0.05% decline in all-cause mortality, whereas for the least prolific (Prolificness = 0) the effect is approximately zero. Most legislatures are still effective: the estimated effect turns negative once prolificness reaches 0.08 on the 0–1 scale.

A potential confounder is the passage of laws unrelated to public health that were enacted around the same time. Such laws could affect educational attainment or income and thereby indirectly reduce mortality. As a proxy for total legislative activity, I collect the number of pages of laws passed in each regular legislative session. Because my measure of public health laws is based on the number of laws rather than pages, I standardize both variables to have mean zero and standard deviation one. In addition, I control for the presence of women's suffrage and alcohol prohibition, both of which have been shown to reduce mortality. The results are presented in Table 5. The OLS estimates suggest that a one standard deviation increase in public health laws reduced mortality by approximately three percent. The coefficients are similar across all four specifications; however, once other laws, women's suffrage, and prohibition are added, the results are no longer statistically significant. The instrumental variables estimates in Panel B suggest that a one standard deviation increase in public health laws decreased mortality by between four and six percent, with all specifications statistically significant at conventional levels. Consistent with the literature, the estimates for women's suffrage and prohibition indicate that both policies reduced mortality, while other general laws did not.

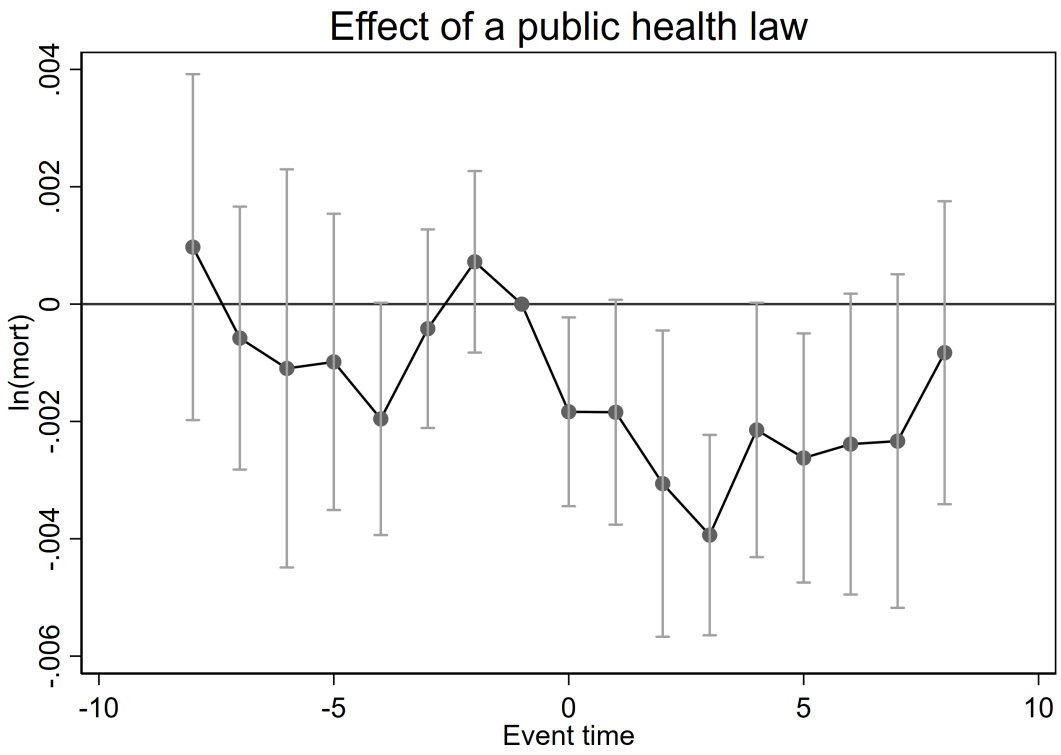
The event-study results appear in Figure 3. Mortality declines following the passage of a public health law, reaching a peak effect of approximately -0.004 log points. Six event-study coefficients are statistically significant, and subsequent estimates remain negative. There is a small, statistically insignificant uptick in mortality two months before a law is passed, suggesting that some laws may have been responses to disease outbreaks. Appendix Figure A.2 reports the event-study results after excluding laws that contain terms suggestive of delayed implementation (e.g., variants of *effective on*). As most laws do not contain such language, the resulting trajectory is similar.

Table 5: Controlling for other laws

	(1)	(2)	(3)	(4)
Panel A: Ordinary Least Squares				
Standardize public health laws	-0.0345***	-0.0279*	-0.0332***	-0.0251
	(0.00564)	(0.0160)	(0.00482)	(0.0165)
Standardize all law pages		-0.00771		-0.00929
		(0.0140)		(0.0148)
Women's suffrage			-0.0597***	-0.0590***
			(0.0169)	(0.0171)
Prohibition			-0.0264**	-0.0302**
			(0.0123)	(0.0124)
Panel B: Instrumental Variables				
Standardize public health laws	-0.0429***	-0.0641***	-0.0420***	-0.0656***
	(0.00749)	(0.0181)	(0.00687)	(0.0175)
Standardize all law pages		0.0196		0.0213*
		(0.0130)		(0.0120)
Women's suffrage			-0.0600***	-0.0618***
			(0.0161)	(0.0168)
Prohibition			-0.0222*	-0.0113
			(0.0134)	(0.0162)
N	556	556	556	556

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p*** < 0.01$.

Figure 3: Local Projection Difference-in-Differences Estimates



Notes:

6 Topic Modeling

The previous section provides evidence that public health laws reduced mortality but offers little insight into which types of laws were most effective. A cursory reading of Fowler's reports reveals a diverse set of laws ranging from the invasive (e.g., involuntary quarantines) to the expensive (e.g., municipal waterworks financing) to the relatively mundane (e.g., bans on public spitting). It seems unlikely that such a varied set of laws would have had equally strong effects on mortality.

To categorize the laws systematically, I use Latent Dirichlet Allocation (LDA), an unsupervised machine-learning technique from computational linguistics (Blei et al., 2003).[7][8] LDA is a mixture model in which each document (law) is represented as a distribution over K topics, and each topic is a distribution over words. The number of topics K is chosen by the researcher. A larger K yields more granular topics, some of which may overlap conceptually, while a smaller K yields broader categories. The purpose of LDA is to classify the laws in a manner useful for the research question at hand; there is no single correct value of K suitable for all applications.

LDA estimates parameters for the following data-generating process. For each topic $k \in \{1, \ldots, K\}$, draw a topic–word distribution $\beta_k \sim \text{Dir}(\eta)$. For each document $d \in \{1, 2, \ldots, D\}$, draw topic proportions $\theta_d \sim \text{Dir}(\alpha)$, where θ_d is a K-dimensional probability vector with elements that sum to one. Let N_d denote the number of words in document d. For each word position $n \in \{1, \ldots, N_d\}$, draw a topic assignment $z_{dn} \sim \text{Multinomial}(\theta_d)$ and then draw a word $w_{dn} \sim \text{Multinomial}(\beta_{z_{dn}})$. Under the bag-of-words assumption (word order is ignored), the vector of word counts in document d is multinomial. LDA yields two objects of interest: $\hat{\theta}_d$ (the estimated topic mixture for document d) and $\hat{\beta}_k$ (the estimated

[7] LDA has several advantages over using a large language model (LLM) such as ChatGPT or Claude to classify the data. The LDA algorithm is transparent, open-source, and therefore replicable, whereas frontier LLMs rely on proprietary systems. Their training data—and in some cases the models themselves—are continually updated and fine-tuned, and their behavior across settings is not fully understood. Hallucinations are well documented, and LLMs can introduce subtle errors that are difficult to detect.

[8] Examples of papers using LDA in economics and the social sciences include Polyzos and Wang (2022) on social-media posts related to energy markets, Edison and Carcel (2021) on FOMC transcripts, and Saavedra (2025) on coverage of women's suffrage.

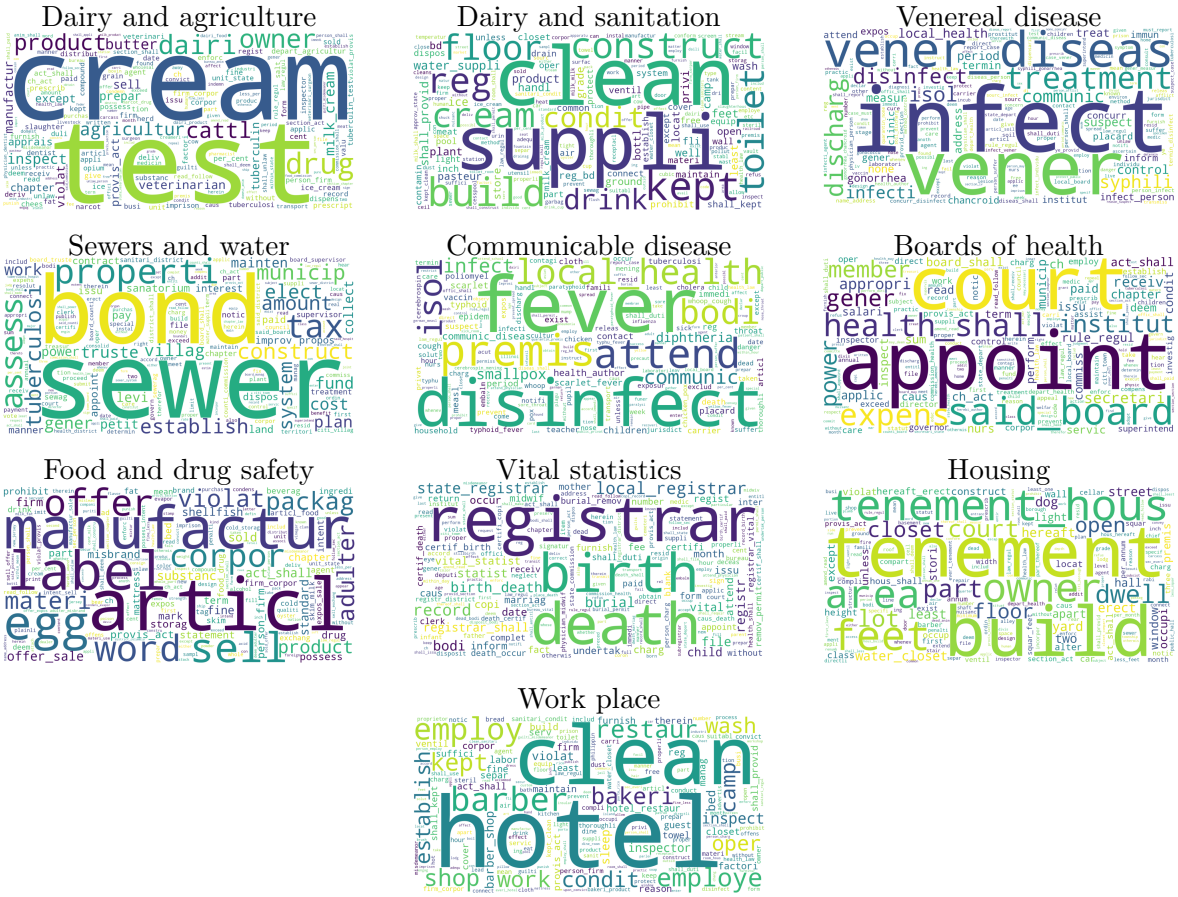
word–topic distribution for topic k).

Before estimation, I apply the following preprocessing steps. First, I remove stop words that typically carry little meaning (e.g., *at*, *the*, or *of*). Second, in the bag of n-grams representation, I include both unigrams and bigrams. Third, I remove words that appear fewer than five times in the corpus of laws. Finally, I apply the Porter stemmer, which reduces related words (e.g., *vaccine* and *vaccines*) to a common stem.

The meaning of topics of can often be determined by displaying word clouds in which the words are proportional to the estimated word-topic probability $\hat{\beta}_k$. The topics appear as word clouds in Figure 4. Each stemmed word or bigram is proportional to the probability of its use within the topic. Topic 1 contains the stems *cream*, *cattle*, *test*, and *dairy*. This topic clearly concerns the inspection and testing of dairy for contaminants, a common practice that Anderson et al. (2025) show reduced deaths from diarrheal disease. Topic 2 also relates to sanitation, including the stems *toilet*, *supply*, and *pasteurization*, which I refer to as general sanitation. Other topics include venereal disease (with the stems *venereal*, *infect*, and *discharge*); water and sewer (containing stems related to water systems such as *sewer*, *municipal*, and *system*, as well as financing terms such as *bond*, *tax*, and *property*); and communicable disease (with the stems *isolate*, *disinfect*, and *fever*). Topic 6 concerns boards of health, with stems such as *appoint*, *power*, and *expense*. Topic 7 addresses the labeling and safety of food and drugs, with stems including *manufacture*, *label*, and *package*. The remaining topics include laws related to the collection of vital statistics (with stems *register* and *record*); housing and tenements (with stems *tenement*, *building*, and *owner*); and workplace regulations (with stems *hotel*, *barber*, *bakery*, and *employ*).

Summary statistics for the cumulative number of laws by topic appear in Table 6. The average state–month has approximately 8 laws in dairy/agriculture and dairy/sanitation; 4 in venereal disease; 9 in sewers/water; 7 in communicable disease; 19 in board of health; 6 in food and drug safety; 4 in vital statistics; 3 in housing; and 5 in health in the workplace. The maximum number of laws in any state–topic pair is 141 (sewers/water). The multitude of health laws, many addressing the same public-health issue, underscores why it is diffi-

Figure 4: Word clouds of topics



Notes:

Table 6: Summary statistics of cumulative laws by topic

Topic	Mean	S.D.	Min	Max	N
Dairy and agriculture	8.1	8.3	0.0	46.9	6,850
Dairy and sanitation	8.2	8.8	0.0	64.4	6,850
Venereal disease	4.1	3.2	0.0	16.2	6,850
Sewers and water	8.7	13.9	0.0	140.6	6,850
Communicable disease	7.2	7.8	0.0	57.9	6,850
Boards of health	18.8	18.1	0.0	111.3	6,850
Food and drug safety	5.9	7.4	0.0	60.3	6,850
Vital statistics	4.4	3.7	0.0	26.1	6,850
Housing	2.5	3.3	0.0	20.3	6,850
Work place	5.2	4.1	0.0	18.5	6,850

Notes: Topics are from a LDA model with $K = 10$. I assigned the topic labels using the word-topic distributions for each topic. The cumulative number of laws are the number of laws in a topic passed at time t in state s since the beginning of sample (June, 1911). A laws are a mixture of topics and law that is, say, 30% in topic k is coded as 0.3 laws for that topic.

cult to identify the effect of any single law type using a staggered difference-in-differences specification with one intervention date per state.

Two-way fixed-effects estimates are reported in Table 7. Because there are ten topics of interest, I use Romano–Wolf p-values to correct for multiple-hypothesis testing. This step-down procedure adjusts the critical values rather than the standard errors, so I report coefficients and p-values instead of standard errors. The results suggest that passage of a food and drug safety law reduces mortality by 0.5%, which is statistically significant at the 10% level. A law related to the collection of vital statistics is associated with a decline in mortality of about 1%, significant at the 1% level. The dairy/agriculture topic has a positive and significant coefficient of 0.003, suggesting that such laws may be responses to milk-related disease outbreaks or to possibly deregulation. No other topics reach conventional significance thresholds after the multiple-testing correction.

7 Cause of death

The top causes of death in the United States changed rapidly during the twentieth century, especially during the first decades. Between 1900 and 1950, the age-adjusted death rate for

Table 7: Two-way fixed effects estimates of topics

	Coef. (1)	p-value (2)
Dairy and agriculture	0.003	0.038
Dairy and sanitation	0.000	0.789
Venereal disease	0.006	0.138
Sewers and water	-0.000	0.597
Communicable disease	0.003	0.123
Boards of health	-0.001	0.501
Food and drug safety	-0.005	0.070
Vital statistics	-0.011	0.001
Housing	-0.007	0.113
Work place	0.004	0.128

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p***< 0.01$.

females fell by 86% between 1900 and 1950 for influenza and pneumonia, 92% for tuberculosis, and 96% for diarrhea and enteritis (Hahn et al., 2018). Deaths from chronic conditions increased, with the age-adjusted death from cancers and cardiovascular disease increasing 32% and 39%, respectively. Similar, and sometimes even starker changes occurred for males (Jones et al., 2020).

Few states reported cause of death at the monthly level during this time period, thus, to aggregate the data to the annual level. Annual-state level cause of death data come from Miller (2006). To allow for every state-year cell to have all twelve month, I drop 1911, for which the law data starts in June. All states that enter the registration during the sample period do so in January of that year. Repeating the OLS and and IV estimation using the annual data yields almost identical results (see Appendix Table A.2.

Table 8 displays the results for 20 separate causes of death. As every cause of death has its own unique age-risk profile, the denominator for every cause is the total population, even for infant mortality and under age-2 diarrhea. Measures deaths with the same denominator implies that that if the coefficient of one cause is larger in magnitude than another, then that law has larger effect on total mortality. Because there are twenty causes of death, I again use the Romano-Wolf p-values corrected for multiple hypothesis testing. Most causes see a decline in mortality during this period. This is not surprising as numerous laws were passed, and

Table 8: The effects of public health laws on cause of death

Cause	OLS		IV	
	coef.	p-value	coef.	p-value
Typhoid	-0.001	0.028	-0.001	0.430
Malaria	-0.002	0.479	-0.002	0.421
Smallpox	-0.002	0.962	-0.003	0.939
Measles	-0.002	0.803	-0.002	0.819
Scarlet fever	-0.003	0.585	-0.003	0.430
Whooping cough	-0.000	0.745	-0.000	0.939
Diphtheria	-0.001	0.260	-0.001	0.430
Influenza	-0.003	0.060	-0.003	0.037
Meningitis	0.002	0.962	0.002	0.939
Diabetes	-0.001	0.154	-0.001	0.430
Circulatory	-0.000	0.908	-0.000	0.430
Pneumonia	-0.001	0.126	-0.001	0.069
Diarrhea (under 2)	-0.003	0.028	-0.003	0.037
Brights nephritis	-0.002	0.004	-0.002	0.002
Suicide	-0.000	0.962	-0.000	0.939
Tuberculosis	-0.001	0.060	-0.001	0.037
Cancer/tumor	-0.000	0.126	-0.000	0.089
Childbirth	-0.000	0.427	-0.000	0.571
Accidents/violence	-0.000	0.199	-0.000	0.430
Infant mortality	-0.001	0.011	-0.002	0.015

most causes would have had at least a subset of laws targeted towards that causes. However, only a few causes see statistically significant declines following the passage of public health laws. For the OLS model, typhoid fever, influenza, diarrhea under age 2, Brights nephritis, tuberculosis, and infant mortality see statistically significant declines. The largest statistically significant declines are for influenza and diarrhea under age 2, suggesting that a public health law reduces the death rate by 0.3 percent. The IV are noisier, with influenza, pneumonia, tuberculosis, Brights nephritis, and infant mortality showing the largest declines. Cancer is marginally significant with a small point estimate.

Tables 9 and 10 report two-way fixed-effects estimates of the ten law topics across the twenty causes of death. Because there are many comparisons, I adjust p-values using the Romano–Wolf step-down algorithm, accounting for the 200 hypotheses tested. As expected with so many tests, adjusted p-values are large and, in general, precision is insufficient to

distinguish effects from noise. Only one coefficient remains statistically significant after the correction: dairy/agriculture laws are associated with an increase in tuberculosis. This pattern is consistent with laws regarding dairy and agriculture responding to outbreaks of bovine tuberculosis, which was common during this era.

Table 9: The effects of law topics on cause of death: First ten causes

	Typhoid	Malaria	Smallpox	Measles	Scarlet fever	Whooping cough	Diphtheria	Influenza	Meningitis	Diabetes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dairy and agriculture	–0.003	0.036	0.032	–0.015	–0.006	–0.005	0.015	0.003	0.030	–0.010
	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)
Dairy and sanitation	0.002	0.000	–0.031	0.009	0.003	–0.003	–0.004	0.003	0.001	0.002
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
Venereal disease	0.009	0.049	–0.035	0.014	0.066	0.026	0.047	0.062	0.026	–0.013
	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)
Sewers and water	0.009	–0.013	0.010	–0.001	–0.005	0.002	0.002	–0.004	0.005	–0.000
	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)
Communicable disease	–0.021	0.021	–0.000	–0.017	–0.001	–0.010	–0.014	0.004	0.012	0.003
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Boards of health	–0.010	–0.009	–0.015	–0.013	0.002	–0.002	–0.012	–0.011	–0.009	–0.002
	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)
Food and drug safety	0.005	–0.017	0.006	0.024	–0.007	0.002	–0.001	–0.003	–0.004	0.001
	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)
Vital statistics	–0.028	–0.045	–0.062	0.034	0.002	0.008	–0.034	–0.042	–0.082	0.007
	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)
Housing	–0.008	–0.029	0.045	0.012	–0.045	–0.028	–0.018	–0.011	–0.005	0.007
	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)
Work place	0.014	–0.011	–0.005	–0.025	–0.009	0.004	0.027	0.026	0.005	0.003
	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)

Table 10: The effects of law topics on cause of death: Second ten causes

	Circulatory	Pneumonia	Diarrhea (under 2)	Brights nephritis	Suicide	Tuberculosis	Cancer/ tumor	Childbirth	Accidents/ violence	Infant mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dairy and agriculture	0.000	0.003	0.005	–0.003	–0.006	0.009	0.002	–0.002	–0.000	0.006
	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)	(0.997)
Dairy and sanitation	0.003	–0.002	0.008	0.002	0.002	–0.003	0.003	–0.003	–0.002	0.001
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
Venereal disease	0.001	0.002	0.014	–0.005	0.001	0.015	–0.000	0.020	–0.002	0.017
	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)	(0.995)
Sewers and water	–0.001	–0.000	0.002	–0.001	0.001	–0.001	–0.001	0.001	0.002	–0.000
	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)	(0.399)
Communicable disease	0.004	0.003	–0.009	0.002	0.003	–0.001	0.002	–0.004	–0.002	–0.001
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Boards of health	–0.001	–0.002	–0.011	0.002	0.001	–0.004	–0.001	–0.000	–0.001	–0.004
	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)	(0.360)
Food and drug safety	–0.000	–0.004	–0.006	–0.005	–0.001	–0.003	–0.001	–0.003	–0.003	–0.008
	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)
Vital statistics	–0.010	–0.014	–0.030	–0.015	–0.002	–0.012	–0.009	–0.006	–0.005	–0.013
	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)	(0.449)
Housing	0.007	–0.009	–0.012	–0.006	–0.002	–0.004	0.002	–0.002	–0.000	–0.017
	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)	(0.992)
Work place	0.002	0.013	0.031	0.008	0.000	0.006	–0.000	–0.001	0.001	0.012
	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)	(0.909)

8 Accounting for Declining Mortality

The preceding sections show that, on average, individual public-health laws generated economically small reductions in mortality. This raises two questions: (1) when aggregated, do numerous public-health laws produce a meaningful decline in mortality? and (2) how much of the 1910s–1920s mortality decline can be accounted for by public-health legislation?

To answer these questions, I first estimate the observed decline in mortality over the sample period and then construct a counterfactual mortality series in which no public-health laws are enacted. I begin by restricting the sample to states who were in the registration area from the start of the sample. This restriction forms a balanced panel, which I then aggregate to a time series. I normalize time to the unit interval, $t' \in [0, 1]$, by setting $t' = \frac{t-1}{T-1}$, for $t \in \{1, 2, \ldots, T\}$.

I then estimate the following regression:

$$\ln m_t \;=\; \alpha_m \;+\; \beta_1 \, \mathbf{1}\{t \in \text{Wave}_1\} \;+\; \beta_2 \, \mathbf{1}\{t \in \text{Wave}_2\} \;+\; \delta \, t' \;+\; \epsilon_t, \tag{4}$$

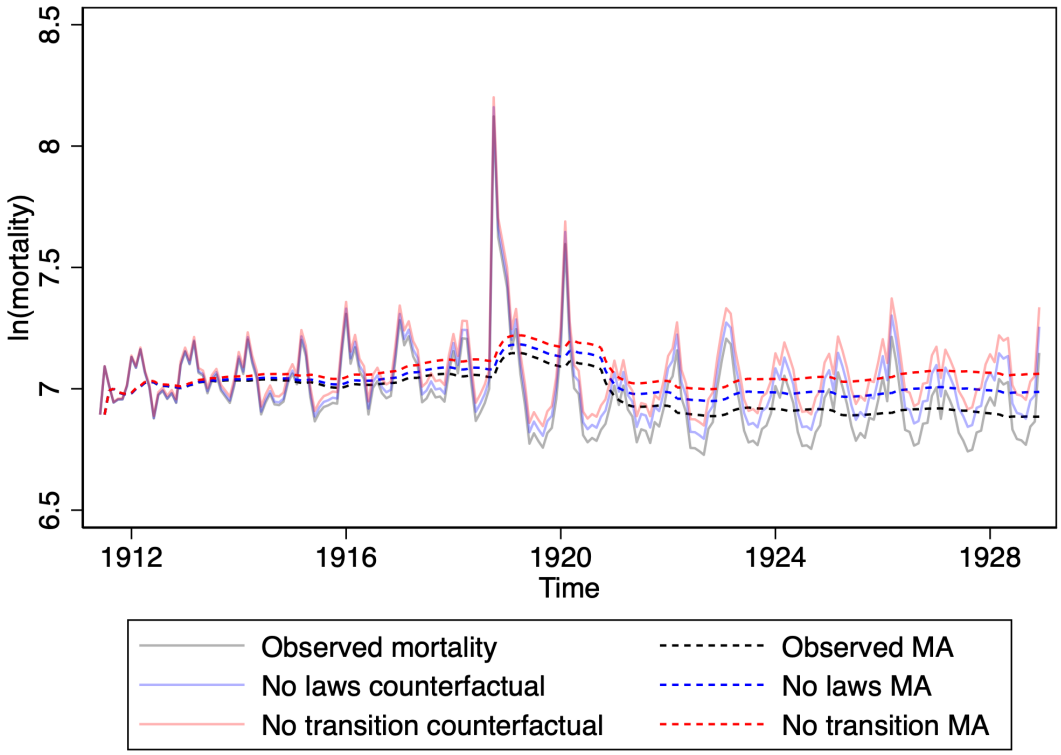
where α_m is a month-of-year fixed effect, $\mathbf{1}\{t \in \text{Wave}_j\}$ for $j \in \{1, 2\}$ are binary variables that absorb the unusual mortality patterns during the first and second influenza-pandemic waves. The coefficient δ captures the linear trend in log mortality over the sample; because $t' \in [0, 1]$, the parameter δ equals the total change log mortality over the period.

From this regression, I construct a counterfactual no-mortality-transition (NMT) series that removes the time trend: $\ln m_t^{\text{NMT}} = \ln m_t - \hat{\delta} t'$. Using the baseline OLS estimates, I construct a no-law (NL) counterfactual by setting $\ln m_t^{\text{NL}} = \ln m_t + 0.0005 cLaws_t$. I then re-estimate equation 4 with $\ln m_t^{\text{NL}}$ as the dependent variable to obtain $\hat{\delta}^{\text{NL}}$, which measures how much mortality would have declined in the absence of any public-health laws.

The estimates imply that mortality declined by 18% over the sample period. Under the no-law counterfactual, mortality declines by only 7%, implying that public-health laws account for 61% of the decline $\left(\frac{11}{18} = 0.61\right)$.

To visualize the cumulative effect of public-health laws, Figure 5 plots the observed mor-

Figure 5: Counterfactual mortality



tality rate, the no-mortality-transition counterfactual, and the no-law counterfactual. To make underlying trends more visible amid seasonality and the influenza-pandemic waves, I also display a 24-month moving average. The no law counterfactual lies closer to the no mortality transition series than to the observed mortality series.

9 Conclusion and Discussion

The results of this paper suggest that laws mattered: even if each statute had a trivial effect, their accumulation produced a meaningful impact. A collection of laws can also be viewed as a measure of the strength of public-health institutions, since it is difficult to imagine a robust public-health institution without legal authority over many aspects of both private and public life.

The causes of death most affected are those with plausible mechanisms: for example, waterborne causes such as childhood diarrhea, and airborne diseases exacerbated by overcrowding in tenements, such as pneumonia and tuberculosis. Furthermore, public-health laws regarding tenements, an area with little quantitative research in economic and demographic history, are strongly associated with reductions in mortality.

There are several caveats. Most notably, I lack measures of municipal public-health laws. City-level laws are not entirely ignored, however, because many state-level public-health statutes regulate what cities may do or compel cities to act in specific ways. In addition, this study does not measure private actions. Private behavior is influenced by law but also by incentives; as knowledge of germ theory spread, people may have altered their behavior, even absent public-health laws, to avoid pathogens.

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Figure A.1: Examples of Public Health Laws

Smallpox—Quarantine. (Reg. Bd. of H., Jan. 13, 1922)

1301. All members of a household where smallpox exists shall be quarantined until released by the local health officer under the following provisions:

(*a*) Before release of a smallpox patient the skin must be free of scabs and the dark-colored plaques, often present under the outer layer of skin of the palms of the hands and the soles of the feet; the patient must take a full bath and shampoo the hair, and all clothing and other articles exposed to infection must be disinfected as directed by the local health officer.

(*b*) Persons. not protected by a recent successful vaccination or an attack of smallpox, residing on premises where smallpox exists or directly exposed by association with a case of smallpox, who refuse to be vaccinated shall be isolated and shall not be permitted to leave the premises until 21 days after last exposure.

(*c*) Persons who are protected by a recent successful vaccination, or an attack of smallpox, or who submit to vaccination within three days after first exposure to smallpox, may be given written authorization by the local health officer to go into and from the premises under quarantine for smallpox.

Shaving Brushes Containing Horse Hair—Manufacture, Possession, Sale, or Distribution of, Prohibited. (Reg. Bd. of H., May 2, 1922)

2000. No person shall manufacture, have, keep, offer for sale, sell, distribute, or give away, in the State of Minnesota, any shaving brush in which horsehair is used in whole or in part.

Table A.1: OLS results controlling for regional trends

	(1)	(2)	(3)
Cumulative laws	-0.000261**	-0.000282**	-0.000558***
	(0.000112)	(0.000107)	(0.0000917)

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p***< 0.01$.

A Appendix

Table A.2: OLS estimates of the effect of public health laws

	(1)	(2)	(3)	(4)
	Panel A: OLS			
Cumulative laws	-0.000559***	-0.000524***	-0.000296***	-0.000526**
	(0.0000913)	(0.000107)	(0.0000690)	(0.000220)
	Panel B: Second stage			
Cumulative laws	-0.000695***	-0.000702***	-0.000457***	-0.000724***
	(0.000121)	(0.000151)	(0.000101)	(0.000180)
	Panel C: First stage			
Cumulative sessions	0.393	0.796*	0.292	-0.080
	(0.496)	(0.421)	(0.476)	(0.570)
Cumulative session × salary	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
F-stat of IVs	357.72	219.91	453.30	74.17
N	557	374	512	557
Balanced	N	Y	N	N
Lagged mortality	N	N	Y	N
Weighted	Y	Y	Y	N

Notes: Statistical significance: $*p < 0.1$, $**p < 0.05$, $p***< 0.01$.

Figure A.2: LP-DiD estimates dropping laws with delayed effects

