Denys Dukhovnov
Human Mortality Database (HMD)
Department of Demography
University of California, Berkeley

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Health Regulation Consequences for Subnational Mortality in the United States, 1990–2018

Extended Abstract

Health and mortality differentials across national and isolated geography are well documented in the past literature (Kindig & Cheng, 2013). Recent advances in small area estimation enabled the generation of high-quality mortality estimates by age and sex enabled deeper subnational analyses of mortality and its differentials (Alexander et al., 2017; Dwyer-Lindgren et al., 2022). Subnational estimates for the United States have been produced by the United States Mortality Database team at both state and county group resolutions (USMDB 2022, 2023; Winant 2021). At the same time, while some effort has been directed toward production of life tables for even smaller geographies, such as census tracts (Boing et al. 2020; NCHS (U.S.) 2018), the factors predicting mortality at an aggregate level at smaller geographic resolution remain understudied.

Like most socio-demographic phenomena, mortality outcomes in the US states and counties are subject to socioeconomic and environmental conditions of a given area. In addition, these could be impacted by knock on effects from spatially proximal geographies and by governing state health policies. One aim of state health regulation is to enable equitable access to primary care, resources, and safety in communities that are otherwise riddled with socioeconomic issues and inequalities, thus improving health and lowering mortality. However, due to differences in qualitative impact and scope of application of policies in different locations and times, it is difficult to gauge and compare the combined effects of health regulation on population mortality outcomes across the country. For instance, public health studies tend to investigate the effects of a particular policy in a particular locality on individuals or small populations. However, examining the effect on subnational mortality over time and across vast geography using disparate and individual policies would ignore the overarching socioeconomic and political trends contributing to overall mortality outcomes.

Objectives

(1) I create a synthetic summary measure for State Health Policy for population-level analyses.
(2) Using new, high quality longitudinal estimates of state- and county-group-level mortality and established spatial econometric modeling approaches, I set out to uncover the collective impact of state health policies over nearly 3 decades (1990–2018) on subnational mortality outcomes.

Data

This analysis employs data from several sources. First, the life table estimates by county for the range of years 1990–2019 are available from United States Mortality Database (USMDB) (USMDB 2022, 2023;

Winant et al., 2021). These mortality estimates were derived from a Bayesian analysis described in (Alexander et al., 2017)) and extended by the USMDB team to include further adjustments and disaggregating the estimates by sex (Winant et al., 2021). Mortality estimates have been generated annually using a fixed county grouping with time-invariant administrative boundaries, for which socioeconomic and demographic data are typically available at decennial censuses. Second, I use a collection of contemporaneous and lagged areal summary indicators at state and county levels from the US Census Bureau decennial censuses and the American Community Survey. Third, I incorporate data summarizing the chronology and nature of adopted state health policies from 3 independent databases: (1) the State Policy Innovation and Diffusion Database (SPID) (Boehmke et al., 2018), (2) the State Policy and Politics Database (SPPD) (Montez, 2022), and (3) Centers for Disease Control data on nutrition, physical activity, and obesity as well as tobacco tax legislation (CDC 2023; CDC 2023b). Fourth, an additional set of state political and ideological affinity measures are drawn from the work of Berry and colleagues (2010) to place the legislative activity in the context of its political climate.

Analysis

To satisfy the first objective, I synthesize a summary State Health Policy (SHP) indicator. For this task I use a set of **110 policies** adopted between 1970 and 2018 that are deemed to be directly responsible for mortality (abortion, traffic injury/death prevention, gun legislation, etc.) or onset of chronic health conditions (smoking, healthy food access, etc.). The scores are created for each state $\boldsymbol{s}$ at time $\boldsymbol{t}$ by subjectively assigning a policy "positivity" score $\boldsymbol{p}$ from the value set $P = \{-1,0,1\}$, whereby (+1) is assigned to a policy that is likely to reduce mortality/improve health, (0) if its impact is ambiguous, and (-1) assigned a policy that would potentially worsen mortality outcomes. Two rounds of weighting are necessary to compensate for the unequal number of policies within 8 thematic groups $\boldsymbol{g}$ and then again within 4 policy classes $\boldsymbol{c}$ so as to prevent overrepresentation (see Table 1).

Table 1. Description of thematic categories and classes of state policies proximal to causes of mortality.

Thematic categories	
1	Traffic and road safety, driving, cycling, etc.
2	Weapons, firearms, violent crime
3	Drug and opioid use, prescription regulation, monitoring and dispensation of controlled substances
4	Abortion, reproductive and maternal health
5	Alcohol and tobacco sale and consumption
6	Health insurance, regulatory acts against medical malpractice
7	Nutrition and safety net
8	Preventive health, screenings and tests, public health programs
Classes	
1	Legal regulation, barriers or limited restrictions
2	Fines, taxes, levies
3	Partial bans or a complete ban on an activity or product
4	Government and community health improvement initiatives

Ultimately, only cumulated data from 1990 onward are used, as not all states have passed enough policies to sufficiently saturate all policy thematic groups and classes in the first 20 years of the observation period.

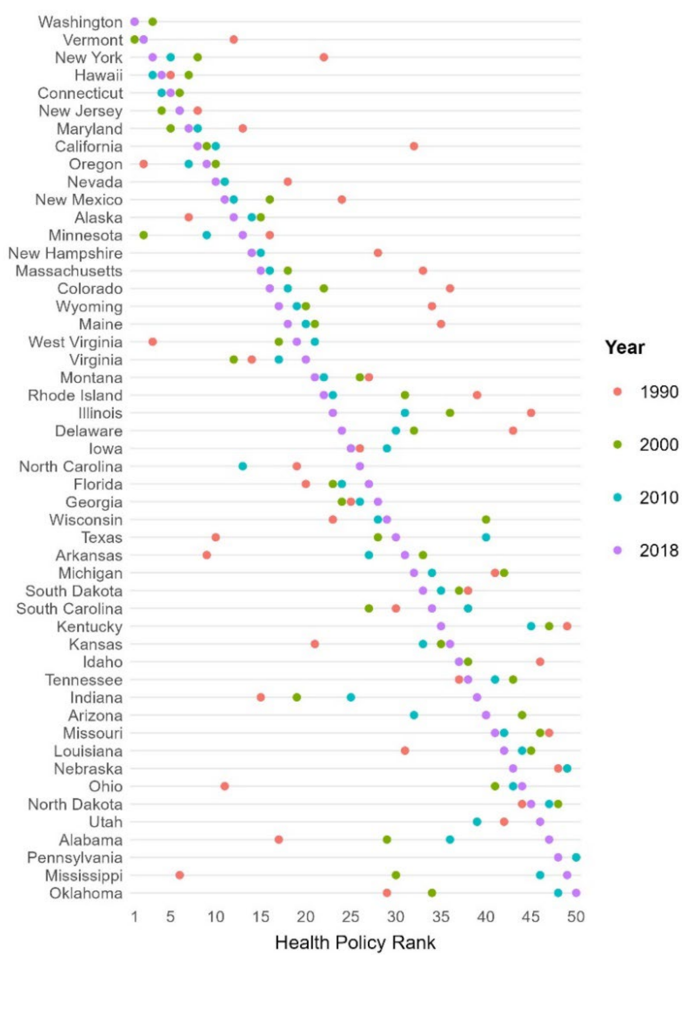
$$R_{gst} = \frac{\sum_{i=1}^{N} p_{igst}}{\underset{s \in \mathcal{S}}{\operatorname{argmax}} \left| \left[\sum_{i=1}^{N} p_{igt} \right]_s \right|}$$

$$I_{st} = \frac{\sum_{c=1}^{C} \sum_{g=1}^{G} R_{gst} \, N_{cst}}{\sum_{c=1}^{C} N_{cst}}$$

The quantity $\boldsymbol{R}$ in the equations above can be thought of as a state-time-specific positivity score relative to the cross-sectional sample maximum. This synthesis of weighted scores results in a measure $\boldsymbol{I}$ that is both cumulative over time and relative, while incorporating a qualitative aspect of health positivity. Its interpretation is therefore best considered in relation to other states and times in the data (e.g., ranked or normalized). Optionally, the $\boldsymbol{I}$ score can be further adjusted by a set of time-variant weights using a range of kernel functions. This would mimic either latency or decay of temporal effectiveness of policies a particular thematic group $\boldsymbol{R_g}$ (that is, some policies are designed to have an immediate and a short-lived impact, whereas other policies are intended for a durable and lasting impact).

Figure 1 presents the ranked SHP results by state. States with the most health-positive policy agenda are ranked higher on the plot. The normalized scores represented by the rankings are then used as inputs for models in the modeling section.

Figure 1. State Health Policy (***I***) proactiveness ranking (1 = best, 50 = worst), by state (1990–2018).



Modeling

To estimate the SHP impact on mortality at state and county-group levels, I run a series of spatial econometric panel models. Additional useful nuances afforded by such models are accounting for spatial dependence and estimation of spillover and/or containment effects due to proximity. For example, instating a tobacco tax or a sales ban in one state may also reduce its consumption in nearby areas. Alternatively, health outcomes in border areas of a state that enacts such policies may be dampened, if the state's residents could easily cross borders to buy tobacco products. For consistency and comparability over time, I compute 3-year moving average age-adjusted mortality rate for each state and county grouping using the 2010 US population as a standard for men and women. Alternative mortality outcomes evaluated in the course of the analysis are life expectancy (LE) at birth and at age 65 for each sex and both sexes combined.

Predicting mortality and health outcomes over time may require a large number of explanatory variables. However, many studies have focused on general proxy indicators that correlate with the broad notion of disadvantage, which in turn impacts health and mortality outcomes on an areal unit level (Barbieri 2022; Vierboom, Preston, & Hendi 2019). Some such measures were selected for the present analysis. These include: contemporaneous and lagged measures of income inequality, such as Gini coefficient, geographic distribution of population by race and ethnicity, Divergence index as a measure of residential segregation, urban and rural locality identifiers, prevalence of poor health, prevalence of blue-collar occupations, as well as median household income and educational attainment.

The inputs are tested in the framework of spatial econometric panel paradigm. The panel is balanced and consists of T = 4 periods and N_c = 2472 county groups and N_s = 50 states (District of Columbia is excluded). Fixed effects specification has been adopted on the basis of spatial Hausman test with spatial "lag" type of spatial dependence. A mixture of queen(1) contiguity and *k*-nearest neighbors weights are computed to identify spatial neighbors. Following a stepwise testing starting from the pooled OLS toward the more complex specifications, the ultimate preferred model specification is 2-way fixed effects Spatial Durbin Model (FE SDM):

$$y_{it} = \lambda \sum_{i \neq j} w_{ij} y_{jt} + x_{it}\beta + \sum_{i \neq j} w_{ij} x_{jt}\,\theta + \alpha_i + u_{it}$$

where β is a vector of directly estimated regressor coefficients, w_{ij} is the vector from a row-standardized spatial weights matrix **W** for neighboring county groups or states $i \neq j$, λ is a global autocorrelation parameter adjusting the strength of the endogenous spatially lagged response $\sum_{i \neq j} w_{ij} y_{jt}$, θ is a vector of coefficients regulating the indirect (local spillover) effect of spatially lagged covariates $\sum_{i \neq j} w_{ij} x_{jt}$, while α_i is a state/county group specific fixed effect, and $u_{it} \sim \mathcal{N}(0, \sigma^2)\; i.i.d.$ nuisance term.

Assuming a normal distribution with minimum and maximum values representing ±3 standard deviations around the mean, respectively, the ***I*** score measure could account for as much as 12.9% of the geographic gap in age-standardized death rate (30% or 2.1 years of LE at birth, and 1.14 years at age 65) in states at two extremes of the health policy proactiveness. At the same time, the magnitude of effect of SHP on county group mortality is roughly half of the state-level impact. However, county group contextual variables and neighboring spillover effects play a much more influential role in explaining county group mortality. Although the effect of SHP on 2 out of 3 indicators of mortality/longevity is similar for males and females, the impact of SHP on state-level e(65) for males is 15% lower, as compared to females. This is in part likely due to the difference in sex-specific life course hazards. More recent health policy cannot fully compensate for earlier exposure to health risk factors among the male population (e.g., greater history of smoking, occupational exposures, etc.).

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