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THE IMPACT OF CHANGES IN COUNTY PUBLIC HEALTH EXPENDITURES ON GENERAL HEALTH IN THE POPULATION

ABSTRACT

We estimate the effect of changes in the per capita expenditures of county departments of public health on county-level general health status. Using panel data on 40 counties in California (2001-2009), dynamic panel estimation techniques are combined with the Lewbel instrumental variable technique to estimate an aggregate demand for health function that measures the causal cumulative impact that per capita public health expenditures have on county-level general health status. We find that a $10 long-term increase in per capita public health expenditures would increase the percentage of the population reporting good, very good, or excellent health by 0.065 percentage points. Each year expenditures were increased would result in approximately 24,000 individuals moving from the "poor or fair health" category to the "good, very good, or excellent health" category across these 40 counties. In terms of the overall impact of county public health departments on general health status, at current funding levels, each annual expenditure cycle results in over 207,000 individuals being in the "good, very good, or excellent" categories of health status rather than the "poor or fair" categories.

THE IMPACT OF CHANGES IN COUNTY PUBLIC HEALTH EXPENDITURES ON GENERAL HEALTH IN THE POPULATION

INTRODUCTION

County-level health measures of mortality and morbidity are becoming more easily available and are being widely used by public health practitioners to track population health (Community Health Rankings & Roadmaps, 2012; California Health Interview Survey, 2012). One summary measure of general health, self-rated health status, is very common in both health-oriented and non-health-oriented surveys, and is also a foundational health measure in *Healthy People 2020* (U.S. Department of Health and Human Services, 2011). However, to our knowledge, there has been no examination to date as to whether this indicator is responsive to changes in the amount of services provided by county departments of public health as measured by public health expenditures per capita.

While no current measure of general health status fully satisfies all of the criteria for the comprehensive measurement of health (Thacker et al., 2006), self-rated health status captures a great deal of information about an individual's health and, in aggregate, population health. Self-rated health status has been found to predict disability, morbidity, mortality, and other illness (Pietiläinen et al., 2011; Idler, Russell, and Davis, 2000; Bopp et al., 2012; Jyhlä, 2009; DeSalvo et al., 2006; Rutledge et al., 2010). Self-rated health status has also been shown to be significantly associated with factors that affect health such as sleep duration, obesity, social connections, and hypertension labeling (Shankar, Charumathi, and Kalidindi, 2011; Imai et al., 2008; Okosun et al., 2001; Prosper, Moczulski, and Qureshi, 2009; Zhang and Ta, 2009; Barger and Muldoon, 2006). In addition, trends in self-rated health status have been examined as a way to describe the evolution of health inequalities (Clarke and Ryan, 2006).

The consistency of self-rated health across annual national health surveys is instructive regarding the reliability of this measure. The two annual national health surveys in the U.S. are the National Health Interview Survey (NHIS) and the Behavioral Risk Factor Surveillance Survey (BRFSS). Other surveys include sections on health, but these are the only two annual national health surveys in the U.S. that are focused on health. A major difference between these two surveys is one of question order. The NHIS asks about a large number of specific health conditions before the self-rated health item occurs. In contrast, the BRFSS only asks questions related to sampling before the self-rated health item occurs. Studies of the impact of question order on responses to self-reported health status items find that, among English speakers, asking the self-reported health status item after questions on specific health conditions, which can be seen as a form of self-education on the specifics of the respondent's own health, results in either no impact or a slightly positive effect on self-reported health status (Crossley and Kennedy, 2002; Bowling and Windsor, 2008; Lee and Grant, 2009; Badawi, Gariepy, and Schmitz, 2012). Thus, we expect that we may find a small shift between the NHIS and the BRFSS, with the NHIS reporting slightly higher levels of health with otherwise similar trends.

Figure 1 shows that this is exactly what occurs. Figure 1 presents a comparison of the time trends in these two surveys from logistic regressions where self-rated health is dichotomized into "good, very good, or excellent health" (healthy) versus "fair or poor health" (unhealthy). Basic demographic controls are included for age (18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75 and higher), sex, race/ethnicity (white, black, Hispanic, other), marital status (married, single, divorced/separated, widowed), and education (less than high school, high school, any college, college graduate and higher). The vertical axis represents the marginal probabilities of being healthy in a given year (relative to 1996), controlling for the above sociodemographics, while the horizontal axis represents years. The two surveys appear to largely mirror each other, particularly during the 2001-2009 periods that we are interested in, with the NHIS trends being consistently higher than those of the BRFSS, as expected.

FIGURE 1 ABOUT HERE

However, the sample sizes of the NHIS and the BRFSS are too small to obtain statistically valid county estimates of self-rated health. Thus, this study uses a state health survey with a question order similar to that of the BRFSS, but which is specifically designed to provide statistically valid estimates at the county level over a relatively long period of time: the California Health Interview Survey (CHIS). The CHIS is also more reliable than the either the NHIS or the BRFSS in its state-level estimates, given its much larger sample size and county stratification.

What patterns might we expect between per capita county public health expenditures and county-level population health status over time? Table 1 presents the activities of county departments of public health in California.[1] Spending on some of the activities listed, such as influenza immunizations, treatment for communicable diseases, disease screening, prenatal care, regulating public drinking water, regulating food service establishments, and others, will clearly have immediate effects on the health status of many individuals and thus, the health status of the population. Other activities, such as population-based prevention activities, will take a longer period of time to impact the health status of individuals. Thus, the impact of any given year of public health expenditures will not only affect the health status of the population in the year the activities funded by public health expenditures were performed, but will also affect the health status of the population for years to come. Any analysis that hopes to capture the relationship between public health expenditures and health status must therefore be able to account for the cumulative impact of public health expenditures on the health status of the population over time.

Previous research examining the relationship between county-level expenditures and health has primarily focused on mortality, and finds that county-level mortality rates, both all-cause and disease-specific, are reduced when expenditure levels of county departments of public health rise (Grembowski et al., 2010; Erwin et al., 2011; Mays & Smith, 2011; Brown, 2013). However, of these studies, only Brown (2013) has attempted to measure cumulative impact. To our knowledge, the current study is the first to estimate the impact of changes in per capita county public expenditures on county-level general health status, where cumulative impact is taken into account.

TABLE 1 ABOUT HERE

METHODS

Conceptual and Econometric Model

The causal link between per capita county public health expenditures and county-level self-rated health is placed in the context of an aggregate demand for health model. We define an aggregate demand for health model is an aggregate version of the individual demand for health model where health status is a function of the price of medical care, income, age, education, and variables affecting preferences for health, such as race/ethnicity (Zweifel and Breyer, 1997).

Since decision making regarding county department of public health expenditures occurs at the county level, the county is used as the unit of analysis.

As noted above, the main hypothesis is that the key variable of interest, per capita county public health expenditures, will positively affect the health status of the population, both contemporaneously and in the future. While it is possible to reformulate the hypothesis to whether per capita county public health expenditures will positively affect the health status of the average individual in the population (as opposed to the health status of the overall population) contemporaneously and in the future, the necessary econometric model, which uses a lagged dependent variable, would require individual-level panel data. Individual-level panel data are not available, therefore the hypothesis is formulated at the population level and available county-level panel data are used.

A standard Koyck distributed lag model is estimated, which assumes that the effect of county public health expenditures is cumulative (Wooldridge, 2003). The cumulative impact is the sum of a contemporaneous impact, and any subsequent future impacts, which are assumed to decline geometrically over time since it may take longer periods of time for some programs to create measureable impacts on individuals with higher levels of health status and the impacts of such programs on individuals with higher levels of health status are likely to be smaller (Bopp et al., 2012). In other words, the cumulative impact of public health expenditures becomes larger over time, but at a declining rate.

The Koyck model can be described as follows:

(1) $$y_t = \alpha + \beta_0 x_t + \beta_1 \lambda x_{t-1} + \beta_2 \lambda^2 x_{t-2} + \cdots + u_t,$$

where y is the percentage of individuals who rate their health as good, very good, or excellent on a five-level health status item (poor, fair, good, very good, excellent), x is county public health expenditures per capita, and λ, where $0 < \lambda < 1$, is the estimated rate of change of the distributed lag. The number of lags included in the model is theoretically infinite, but practically, the number of relevant lags depends on the size of λ. Larger values of λ yield lag structures where relatively large coefficients are present further and further back in time (in other words, the impact of public health expenditures is substantial for a longer period of time in the future). Additional parameters to be estimated are represented by α and β. Finally, u_t is the error term. To simplify, we lag equation (1) by one period, multiply it by λ, subtract this lagged equation from equation (1), and then rearrange:

(2) $$y_t = \alpha_0 + \beta_0 x_t + \lambda y_{t-1} + v_t \,,$$

where $v_t = (u_t - \lambda u_{t-1})$ and $\alpha_0 = \alpha(1 - \lambda)$. Other public-health researchers have also taken a dynamic approach in recent research (Macinko et al, 2011). The cumulative or long-run impact can be determined by substituting long-run values of both county-level general health status and per capita county public health expenditures into the above equation. We define y^* as the long-run value of y and x^* as the long-run value of x. Substituting these values into equation (2) yields the following equation:

(3) $$y^* = \alpha_0 + \lambda y^* + \beta x^* \,.$$

We then solve for y^*:

(4) $$y^* = \alpha_0 /(1-\lambda) + [(\beta)/(1-\lambda)]x^*.$$

To determine the long-run cumulative impact of increasing (or decreasing) per capita county public health expenditures, we take the first derivative with respect to *x**:

(5) $$\frac{\partial y^*}{\partial x^*} = \beta /(1-\lambda).$$

Many readers will recognize this as the standard result for the sum of an infinite geometric series where $0 < \lambda < 1$. This can also be referred to as the long-run propensity (LRP) ((Wooldridge, 2003). The short-run propensity (SRP), or initial impact, can be defined as β alone.

In order to be empirically estimated, equation (2) must be adjusted in order to include standard factors relevant to the aggregate demand for health. As noted above, these include the price of medical care, income, age, education, and factors that influence population preferences for health, such as race/ethnicity. Prices of medical care can be proxied using the proportions of the population covered by health insurance including Medicaid and related programs, Medicare, and private health insurance. Income is measured as per capita income. Age is measured by the age structure of the population (proportion of the population in the following ranges: 0-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85 and older). Education is measured by the extent to which the population has a college education, which is measured by the proportion of the population who have a bachelor's degree or higher. The racial/ethnic structure of each county's population is measured by the proportion of individuals in each racial/ethnic group (White, Black, Hispanic, Asian/Pacific Islander, Other).

None of the variables used in the analysis are age-adjusted. We follow the approach of Rosenbaum and Rubin (1984), who note that when using an age-adjusted population rate as a dependent variable in regression analysis, all independent variables must also be age-adjusted in order to avoid biased parameter estimates. When age-adjusted variables are not available for every variable in the model, they show that using crude population rates for both the dependent and independent variables, while adjusting for age by including variables indicating the proportion of the population in each age category, will yield consistent estimates.

We include per capita public health expenditures to complete the description of the institutional context. County health expenditures in California are formally categorised into four reporting categories (public health, medical care, drug and alcohol abuse, and mental health). Note that these categories all represent health expenditures that flow through each county government. Because each of these is endogenous in our model (at least subject to omitted variable bias and measurement error), we only include public health expenditures following Angrist and Pischke (2009) who recommend omitting uncorrected endogenous variables in instrumental variables equations. All control variables (health insurance, income, age, education, race/ethnicity) in the model are lagged in order to render all control variables strictly exogenous or weakly exogenous (predetermined).

Two variables in the model are endogenous to the percentage of the population reporting good, very good, or excellent health: the lagged dependent variable and per capita county public health expenditures. The main aspects of endogeneity with regard to per capita county public health expenditures are omitted variable bias and measurement error. For example, the equation does not contain information on varying health policy ordinances, varying environmental conditions, varying population health behaviors, or other factors that may correlate with both self-rated health and county public health expenditures. See the discussion below regarding per capita county public health expenditures being measured with error. These two endogenous variables, the lagged dependent variable and per capita county public health expenditures, can be handled in at least three ways. One is through standard instrumental variables. However, standard instrumental variables are often unavailable or too weak. In these cases, at least two alternative approaches are available. One is the generalized method of moments (GMM) system estimator, which is designed for panels with a small number of time periods and a large number of observations within each time period where it is not assumed that adequate instruments are available outside of the core data set (Roodman, 2009). However, if the available valid instruments (lagged levels and lagged differences) used by the GMM system estimator (Blundell and Bond, 1998) are weak, the result can be significant parameter bias, similar to that found in traditional instrumental variable models with weak instruments (Bun and Windmeijer, 2010). Only ad-hoc methods of testing for weak instruments are currently available when using the GMM system estimator (Bazzi and Clemens, 2013).

An alternative approach that allows traditional weak instrument testing and also does not require outside instruments is that of Lewbel (2012). Lewbel's approach was disseminated through working papers prior to publication resulting in a large number of studies being published that applied Lewbel's methodology both before and after the formal publication of Lewbel's methodology (Stifel and Alderman, 2006; Block, 2007; Sabia, 2007a, 2007b, 2007c; Kelly and Markowitz, 2009; Haung, Lin, and Yeh, 2009; Drichoutis et al., 2012; Kelly et al., 2012; Emran and Shilpi, 2012; Lewbel, 2012; Schroeter, Anders, and Carlson, 2013; Denny and Oppedisano, 2013; Huang and Xie, 2013).

Lewbel (2012) uses any heteroscedasticity present in the data to generate sets of valid instruments. Lewbel's approach does not identify the endogenous variables in the second-stage equation based on traditional exclusion restrictions. Rather, he achieves identification using higher moments. Sufficient conditions for Lewbel's method to be applied are as follows: $Cov(Z, \varepsilon_1 \varepsilon_2) = 0$, $E(X\varepsilon_1) = 0$, and $E(X\varepsilon_2) = 0$, where Z is a subset of *X*, the vector of exogenous variables in the second-stage (and *Z* may include all of *X*) along with some heteroscedasticity in ε_1 and ε_2, the errors from both the first and second stages of a standard IV regression. As noted by Lewbel (2012), a standard overidentication test can be used to evaluate the validity of these assumptions.

Potentially valid instruments are constructed by multiplying the heteroscedastic residuals from the first-stage regressions with a subset (or all) of the mean-centered exogenous variables, $(Z - \overline{Z})\hat{\varepsilon}_1$, where $\hat{\varepsilon}_1$ is the vector heteroscedastic residuals from the first-stage regressions, and $\overline{Z}$ is a vector of the means of *Z*.

These generated instruments may be weak or strong, depending on the degree of scale-related heteroscedasticity in the data. Heteroscedasticity can be detected using a standard Breusch-Pagan type test (Lewbel, 2012). The strength of the generated instruments can be evaluated using standard weak instrument tests (Stock and Yogo, 2005). Since this approach may produce a mix of strong and weak instruments, it is valuable to remove weak instruments from the set of instruments used. The approach taken here is to remove instruments as needed if the absolute value of the instrument's *t*-statistic is less than 1.96 in both of the first-stage regressions.

A final point is that when using panel data, two independent panels can be spuriously associated if they both have unit roots (Granger and Newbold, 1974, Wooldridge, 2003). We therefore test for the existence of unit roots using a test that assumes that the number of units, *N*, can be constant, since counties are unlikely to be added to California. In particular, we perform Phillips–Perron (1988) tests, which use Newey-West (1987) standard errors to account for any serial correlation. The null hypothesis is that the data follow a random walk with or without drift. We use the *z*-statistic as our test statistic, which is recommended by Choi (2001) as offering the best trade-off between size and power. Following the recommendation of Levin, Lin, and Chu (2002), all series are first demeaned by subtracting the cross-sectional means to mitigate the influence of cross-sectional dependence.

All analyses are performed using Stata 11 and *ivreg2* using two-step feasible generalized method of moments (GMM) estimation and ordinary least squares (OLS) for comparison purposes (Lewbel, 2012; Baum, Schaffer, and Stillman, 2010). After generating IVs from non-clustered, heteroscedastic regressions, we cluster our data by county to correct for any downward bias in the standard errors from the presence of any serial correlation following the suggestion of Angrist and Pischke (2009). Petersen's (2009) work on panel data also suggests clustering by county to avoid biasing the standard errors when seeking to take into account both the correlation of observations within clusters and the correlation of observations within time periods, with the latter being taken into account parametrically (by including time dummies). The cumulative impact of county-level per capita public health expenditures is then estimated by evaluating the overall non-linear combination of $[(\beta_0)/(1-\lambda)]$ from equation (5) above.

Data

Self-rated health status at the county-level comes from the California Health Interview Survey (CHIS), which is fielded biennially (California Health Interview Survey, 2012). Health status is measured from high to low in five categories as excellent, very good, good, fair, and poor. Categories are collapsed in accordance with the common practice of dichotomising the variable into two categories: poor/fair and good/very-good/excellent. Thus, the county-level measure is the percentage of individuals in the county with good, very good, or excellent health status.

Information on the per cent of the population with Medicaid or other public insurance, the per cent of the population with Medicare, per cent of population with private insurance, and the per cent of the population with a bachelor's degree or higher also come from the CHIS. The CHIS is designed to yield statistically valid county-level measures for 41 of California's 58 counties. The survey incorporates large statistically-valid samples in each county from all age groups including children, teens, and adults. However, subsetting self-rated health status by race/ethnicity was not feasible as sample sizes then became small and statistically unstable in many counties. For this reason subgroup analysis by race/ethnicity was not performed.

Data was obtained on county-level expenditures for public health from the 2001, 2003, 2005, 2007, and 2009 versions of the *Counties Annual Report* issued by the California State Controller's Office. The *Counties Annual Report* details county expenditures, including public health expenditures (California State Controller's Office, 2011). The report separates county health expenditures into four categories: public health, medical care, mental health, and drug and alcohol abuse. It is not possible to disaggregate county health expenditures further using this report. The determination of how services are categorised across these four classes is a county decision and not all counties categorise services in the same way. Thus, county public health expenditures are subject to some degree of measurement error.

San Francisco, the only county in California that is also a city, is included in the *Counties Annual Report*, but is accorded a separate appendix due to its combined city-county functions.

Because of its unique organisational structure, its expenditures are difficult to compare with the expenditures of other counties. It was therefore omitted from the analysis. The remaining 40 out of 58 counties represent approximately 96 per cent of the population of California.

The proportions of the population in nine age groups (0-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85 and older) and in five racial/ethnic categories (White, Black, Hispanic, Asian/Pacific Islander, and other race) come from the US Census (RAND, 2012). Per capita income comes from the US Bureau of Economic Analysis. All dollar figures are adjusted for inflation and reported in constant 2009 dollars. The analysis includes a total of 199 observations, 40 county-level observations for each year (with the exception of one county for which some data elements were unavailable for one year). The years included are 2001, 2003, 2005, 2007, and 2009.

Results

Table 2 presents descriptive statistics. There is a very large variation in our dependent variable both between counties and within counties. The per cent of the population reporting good, very good, or excellent health status ranges from 68.7 per cent to 90.7 per cent. Within-county standard deviations range from 0.30 per cent to 5.63 per cent with a median of 1.7 per cent showing that there is plenty of movement in general health status within counties for the model to capture.

TABLE 2 ABOUT HERE

Table 3 presents the results of the Lewbel instrumental variable (IV) dynamic panel model and the same dynamic panel model estimated using ordinary least squares. A precondition of either model is that each variable in the model not have a unit root. For every variable in the model, Phillips-Perron tests rejected the null hypothesis that every panel contained a unit root ($p \leq 0.05$). An initial estimation of the Lewbel IV model was performed and all instruments were removed where the *t*-statistic was less than 1.96 in both of the first-stage regressions. This was sufficient to reject underidentification and weak instruments in the second stage, with the overidentification test not rejecting instrument exogeneity. However, in order for the estimated covariance matrix of moment conditions to achieve full rank in the first-stage regressions, one additional instrument needed to be removed. The final Lewbel IV model shows that the null hypothesis of model underidentification is rejected (χ^2=30.71, p=0.02), the null hypothesis of weak instruments is rejected (Kleibergen-Paap rk Wald *F*-statistic = 54.55, which is larger than the critical value for 5% maximal IV relative bias, 20.33, and larger than the critical value for 10% maximal IV size, 43.22), but the null hypothesis that the identifying instruments are exogenous (overidentification test) is not rejected (χ^2=21.08, p=0.18). The model is statistically valid.

However, the OLS model yields very similar results indicating that the OLS model is not severely affected by the biases that the instrumental variable model was intended to correct. In both models, most of the impact on general health status occurs in the year that funds are expended, with a small residual occurring across future years. Both models suggests that, over the long run, a $10 increase in per capita county public health expenditures in a given year would increase the percentage of the population reporting good, very good, or excellent health by 0.065 percentage points. This annual increase in an annual expenditure cycle would impact approximately 24,015 individuals across the 40 counties. Assuming no diminishing returns in the relationship between county public health expenditures and health status, county public health activities funded at current levels improve the health status of approximately 0.56 percent of the population (0.56 = 0.065 x 8.539) with each annual expenditure cycle impacting approximately 207,000 individuals (0.0056 * 36,945,637 estimated population in 40 counties in 2009). If diminishing returns are present, this is an underestimate.

TABLE 3 ABOUT HERE

In both models, higher concentrations of Blacks and Asian/Pacific Islanders were associated with lower population health. This is consistent with California individual-level estimates that show that both Blacks and Asian/Pacific Islanders are more likely to report poor or fair health relative to Whites (California Health Interview Survey, 2011). In contrast, both models found that higher rates of college education (bachelor’s or higher) were associated with greater population health, consistent with major findings in the literature on the individual-level relationship between education and health (Eide and Showalter, 2011). Finally, an upward trend in general health status was also apparent, on average, across these 40 counties. Note that, when considering the associations of the control variables with the dependent variable, the relationships found in county-level models will often be different from the relationships that would be found in individual-level models. This is known as the aggregation problem in econometrics (also called the ecological fallacy problem in sociology) (Chan, 2005). Only the instrumented relationships in the model are corrected for bias and these variables only measure aggregate relationships.

Discussion

We estimated the short-term and long-term effects of county public health expenditures on the percentage of the population reporting good, very good, or excellent health status over a nine-year period (2001-2009) using a standard Koyck model of dynamic relationships. The main finding is that a long-term $10 annual increase in per capita public health spending in the 40 counties examined in California (representing 96% of the population) would move the health of approximately 24,000 individuals from the “poor or fair” category to the “good, very good, or excellent” category each year the increase was in place. The annual cumulative effect of current expenditure levels of county departments of public health is 207,000 individuals being in the “good, very good, or excellent” categories of health status rather than the “poor or fair” categories.

The size of this impact is directly related to the proportion of the population that is primarily served by county departments of public health. The size of this proportion will vary depending on the population characteristics of a given county.

Although the cost of this change in population health may appear to be implied, the cost related to changes in general health status is also related to changes in mortality (Brown, 2013). The relationship between per capita public health expenditures and mortality exhibits a much longer cumulative time period than the cumulative time period implied by the current model. This is actually quite consistent with the large literature that finds that changes in general health status tend to precede mortality (DeSalvo et al, 2006). It thus appears that the activities of county public health departments in California in a given year may initially impact the general health status of the population (having a cumulative impact on approximately 207,000 individuals) and, over a longer time period (approximately a decade), decrease mortality in the population (approximately 26,000 deaths avoided) (Brown, 2013). This repeats each year. The extent to which those whose deaths are averted are the same individuals whose general health status was improved earlier is unknown at the current time, although we suspect that there is a very large overlap.

There are at least two limitations to this study. The first is that this study only examined movement between the combined set of the two lowest levels of general health status and the combined set of the three highest levels of general health status, and thus necessarily did not capture any relationship between per capita public health expenditures and positive movement within the set of the two lowest levels of general health status or positive movement within the set of the three highest levels of general health status.

An additional limitation to this study is that, although the time period used in this study was relatively long (almost a decade), it is possible that a longer time period may yield somewhat different results. For example, some spending on chronic disease prevention may not be fully reflected. This may affect the magnitude of the estimates.

Public health activities are of significant societal value and should be recognised as such. This study is one among many recent studies that are beginning to demonstrate this to the larger health policy community. The current study highlights the overall average effectiveness of public health activities in improving population health, but is unable to address important additional questions, such as what the most cost-effective bundle of public health services may be. In order to move in this direction, publicly available data on public health expenditures are needed where public health expenditures are disaggregated into more subcategories. In addition, publicly-available information is needed on the various subpopulations that primarily receive services within each subcategory. Such information could be acquired by the state implementing specific reporting requirements, developed in cooperation with county public health departments. Movement in this direction would facilitate research to determine the county public health activities that are most cost-effective so that funding can be expanded in areas that are found to yield the best outcomes.

Footnotes

1. In California, county departments of public health activities are financed primarily from taxation and intergovernmental transfers from state and federal governments with user fees and other sources of funding making up the balance (California State Controller's Office, 2011). The level of public health expenditures varies across counties because, although expenditures for some programs and activities are based on federal funding formulas or are required by legislation, county governments largely make their own decisions regarding resource allocation.

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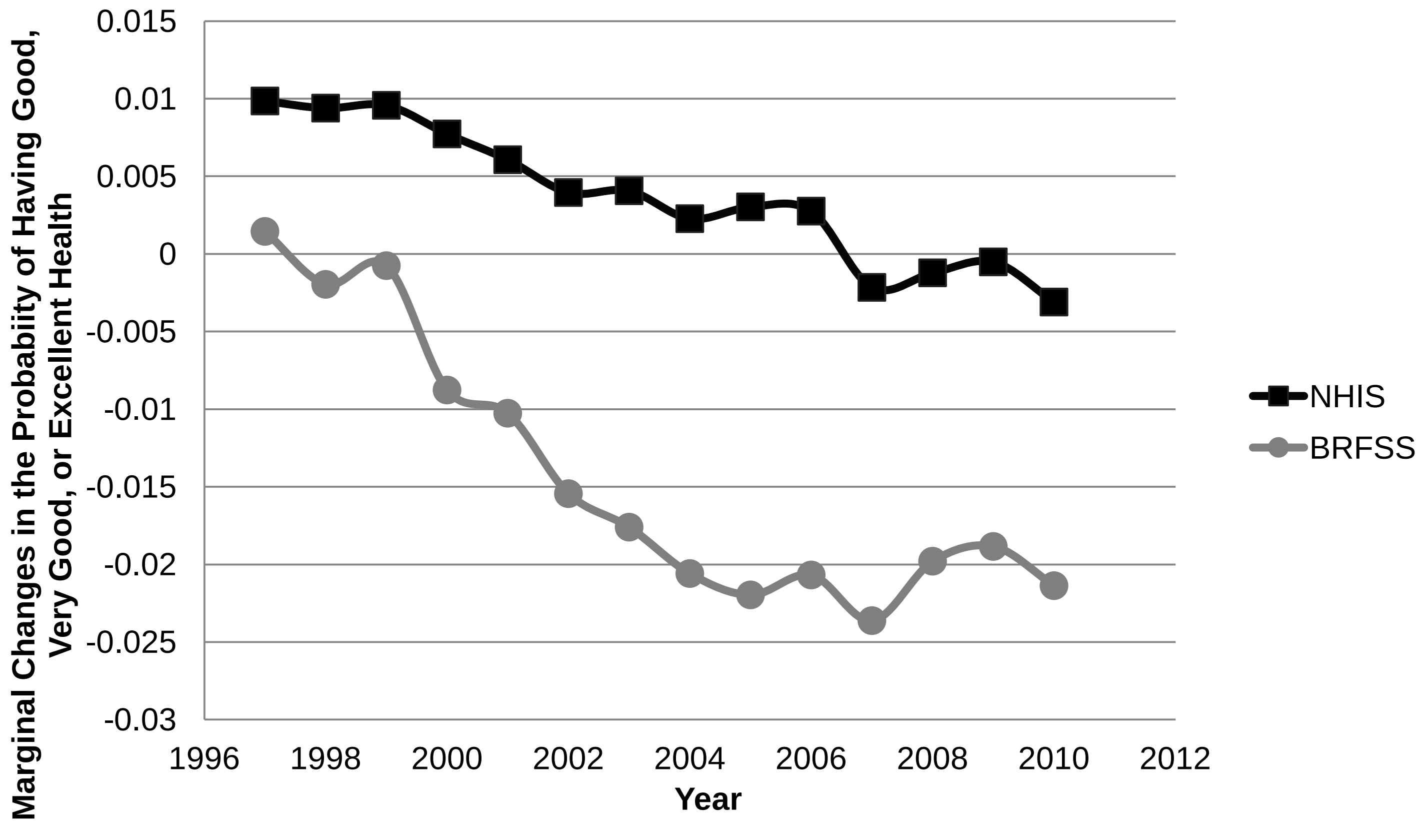
Figure 1. Comparison of General Health Status Trends in Annual U.S. National Health Surveys



NHIS: National Health Interview Survey.

BRFSS: Behavioral Risk Factor Surveillance Survey.

Figure based on logistic regressions controlled for age, sex, race, education, and marital status.

Table 1: Activities of California County Departments of Public Health

Activities	*Per cent Providing*
Screening for diseases/conditions	
HIV/AIDS	86
Other STDs	82
Tuberculosis	95
Cancer	30
Cardiovascular disease	20
Diabetes	26
High blood pressure	39
Blood lead	58
Treatment for communicable diseases	
HIV/AIDS	36
Other STDs	80
Tuberculosis	84
Immunization	
Adult Immunizations	95
Childhood Immunizations	95
Maternal and Child Health (MCH)	
Family planning	61
Prenatal care	30
Obstetrical care	18

Special Supplemental Nutrition Program for Women, Infants and Children (WIC)	73
MCH home visits	89
Early and Periodic Screening, Diagnosis, and Treatment (EPSDT)	50
Well Child Clinic	39
Other Health Services	
Comprehensive primary care	26
Home health care	2
Oral health	23
Behavioral/mental health services	27
Drug and alcohol abuse services	27
Population-based Primary Prevention Activities	
Injury	65
Unintended pregnancy	70
Chronic disease programs	67
Nutrition	88
Physical activity	60
Violence	36
Tobacco	88
Substance abuse	40
Mental illness	33

Epidemiology and Surveillance Activities	
Communicable/infectious disease	98
Chronic disease	64
Injury	64
Behavioral risk factors	51
Environmental health	75
Syndromic surveillance	66
Maternal and child health	93
Regulation, Inspection and/or Licensing Activities	
Mobile homes	5
Campgrounds & RVs	21
Solid waste disposal sites	60
Solid waste haulers	59
Septic systems	55
Hotels/motels	28
Schools/daycare	44
Children’s camps	45
Cosmetology businesses	12
Body art (tattoos, piercing)	45
Swimming pools (public)	67
Tobacco retailers	53
Smoke-free ordinances	65
Lead inspection	61

Food processing	31
Milk processing	14
Public drinking water	60
Private drinking water	50
Food service establishments	70
Health-related facilities	35
Housing (inspections)	47
Other Environmental Health Activities	
Indoor air quality	20
Food safety education	70
Radiation control	14
Vector control	47
Land use planning	45
Groundwater protection	55
Surface water protection	52
Hazmat response	44
Hazardous waste disposal	45
Pollution prevention	37
Air pollution	7
Noise pollution	19
Collection of unused pharmaceuticals	16
Other Activities	
Emergency medical services	37

Animal control	25
Occupational safety and health	19
Veterinarian public health activities	20
Laboratory services	73
Outreach and enrollment for medical insurance (include Medicaid)	70
School-based clinics	28
School health	21
Asthma prevention and/or management	47
Correctional health	35
Vital records	86
Medical examiner's office	2

Source: 2010 National Profile of Local Health Departments

Table 2. Descriptive County-Level Statistics: 2001, 2003, 2005, 2007, 2009 (n = 199)

Variables	*Mean*	*Std. Dev.*
Public health expenditures per capita ($10s in 2009 dollars)	8.539	4.699
Per cent of population with health status that is good, very good, or excellent	81.006	4.874
Proportion of population ages 0 to 14	0.214	0.033
Proportion of population ages 15 to 24	0.150	0.030
Proportion of population ages 25 to 34	0.127	0.022
Proportion of population ages 35 to 44	0.142	0.016
Proportion of population ages 45 to 54	0.139	0.018
Proportion of population ages 55 to 64	0.099	0.022
Proportion of population ages 75 to 84	0.040	0.009
Proportion of population ages 85 or older	0.015	0.004
Proportion of population with Medicaid/other public insurance	0.174	0.071
Proportion of population with Medicare	0.126	0.032
Proportion of population with private insurance	0.629	0.113
Proportion of population that is Hispanic	0.043	0.035
Proportion of population that is Black	0.298	0.156
Proportion of population that is Asian/Pacific Islander	0.087	0.069
Proportion of population that is Other Race	0.018	0.014
Proportion of population with bachelor’s degree or higher	28.186	11.012
Per capita income ($10,000s in 2009 dollars)	3.983	1.274

Table 3. Aggregate Demand for Health: Distributed Lag Model

Explanatory Variables	Lewbel IV		OLS	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Public health expenditures per capita	0.058	4.12	0.053	2.00
Lagged health status (% pop with good, very good, excellent)	0.120	1.73	0.175	1.80
Lagged proportion of population ages 0 to 14	20.560	1.77	23.313	1.69
Lagged proportion of population ages 15 to 24	-11.931	-1.08	-0.330	-0.02
Lagged proportion of population ages 25 to 34	-30.477	-1.86	-12.855	-0.64
Lagged proportion of population ages 35 to 44	-17.727	-0.60	-20.756	-0.62
Lagged proportion of population ages 45 to 54	50.227	2.07	49.317	1.42
Lagged proportion of population ages 55 to 64	-71.170	-2.46	-59.930	-1.52
Lagged proportion of population ages 75 to 84	18.028	0.19	82.556	0.76
Lagged proportion of population ages 85 or older	19.123	0.14	-116.744	-0.70
Lagged proportion of population with Medicaid/other public	-16.095	-2.17	-13.540	-1.27
Lagged proportion of population with Medicare	-8.945	-0.51	-14.551	-0.80
Lagged proportion of population with private insurance	1.434	0.27	0.749	0.11
Lagged proportion of population that is Hispanic	-1.107	-0.32	-2.785	-0.65

Lagged proportion of population that is Black	-9.679	-3.37	-9.592	-2.62
Lagged proportion of population that is Asian/Pacific Islander	-12.666	-2.73	-12.183	-2.33
Lagged proportion of population that is Other Race	-12.853	-0.66	-3.030	-0.12
Lagged proportion of population with bachelor's or higher	26.039	4.81	22.088	3.79
Lagged per capita income ($10,000s in 2009 dollars)	-0.716	-1.92	-0.142	-0.35
Year 2005	2.157	5.45	2.423	5.25
Year 2007	2.406	3.92	2.826	4.08
Year 2009	3.726	3.87	3.831	3.25
Constant	74.202	4.63	63.314	3.56
F-statistic	298.80		54.07	
Hansen's *J* (χ^2) overidentification test (*p*-value)	21.08 (*p*=0.18)		-	
Stock-Yogo weak instrument test				
Kleibergen-Paap rk Wald *F*-statistic (must be larger than critical values below)	54.55		-	
5% maximal IV relative bias, critical value	20.33		-	
10% maximal IV size, critical value	43.22		-	
Underidentification test (χ^2) (*p*-val.)	30.71 (*p*=0.02)		-	

Short-run propensity (*p*-val.)	0.058 ($p \leq 0.01$)	0.053 ($p=0.05$)
Long-run propensity (*p*-val.)	0.065 ($p \leq 0.01$)	0.065 ($p=0.05$)
Observations	159	159

[a]Year fixed effects included, but not reported. [b] 5% or lower statistical significance (two-tailed test).

Note that one age category (ages 65-74) one insurance category (uninsured), one education category (less than bachelor's degree), one racial/ethnic category (proportion of the population that is White, and one year category (year 2003), are omitted to avoid perfect multicollinearity.