The Effect of Physician Supply on Rural Community Health: 1980-1988

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Abstract

This paper investigates the effect of physicians on community health of rural area. OLS models and fixed effect panel models are estimated using data at county level from 1980 to 1988. Ordinary least square results replicate the qualitative findings of previous work, but fixed effect models indicate a *negative* relationship between physicians and community health. Explanations have been made from different standpoints.

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Introduction

Input of manpower in the health care system such as physicians is believed to be an important way of improving population health. However, a considerable proportion of population in rural areas in United States has limited access to health care. The misdistribution of physicians has been a concern to policymakers at the federal, state, and local levels. Various programs are implemented to increase the physician supply in underserved communities such as The National Health Service Corps (NHSC). Other federal programs providing grants and subsidies are intended to bolster the physician supply in these areas. Thousands of health professionals and billions of dollars have been invested on these programs to increase physician supply in underserved communities every year (Holmes, Konrad, and Slifkin, 2001) Research has been done to investigate the effect of these programs on physician supply. All these programs are based on the assumption that physicians contribute to population health status. But how much they contribute? How important a role are physicians playing in the improvement of population health status? If physicians have relatively low effect on the improvement of population, the resources invested in all these programs might not be justified. Little attention has been given to the effect of physicians on population health. Suppose that the effect of physicians on community health is not as important as people thought, then a vast degree of investment on increasing physician supply could potentially be a great waste. In this case, the population would be better off if the resource is used in more important aspects such as hospital construction or health research. A good understanding of physicians' effect on population health will be crucially important to policy makers in making decision about physicians' supply programs, which are usually very expensive to the nation. This paper presents the effect of physicians on the population health status. The paper uses data of 2375 counties in the United States from 1980 to 1988. Disease rate and mortality rate are chosen to measure the health in a given community. Physician ratio is created as the ratio of number of physicians to the population. Characteristics of medical care system social demographic controls are considered. By applying Ordinary Least Squares and panel estimation, the paper investigates the effect of physicians' effect on population health.

Literature Review / Background

Health can be viewed as one form of human capital. The costs of the investment include direct outlays on market goods and the opportunity cost of the time that must be withdrawn from competing uses. This framework has been used by Becker (1967) and Ben-Porath (1967) to develop models that determine the optimal quantity of the investment in human capital at any age. Grossman (1972) constructs a model of the demand for health. The central proposition of the model is that health can be viewed as a durable capital stock that produces an output of healthy time. A person determines his optimal stock of health capital at any age by equating the marginal efficiency of this capital to its user cost in terms of the price of gross investment. Graphically, each person has a negatively inclined demand curve for health capital, which relates the marginal efficiency of capital to the stock and to an infinitely elastic supply curve. The equilibrium stock is determined by the intersection of the two functions. The model explains variation in both health and medical care among persons in terms of variation in supply and demand curves for health capital. Although this work focused on an individual's demand for health, aggregation of individual's demand curves defines a community health function.

As mentioned above, there has been considerable work on the geographic supply of physicians. This work has been motivated by an implicit assumption that geographic access to health care providers is an important input into the health production function for individuals. Newhouse, Williams, Bennett, and Schwartz (1982a), in a seminal paper in this field, point out that the competitive forces play a major role in determining where physicians choose to practice. The data for their analysis is obtained from the American Medical Association Physician Masterfile. Their basic model is that in equilibrium, physicians will be distributed in such a way that (1) Physicians of a given type will everywhere serve the same size population and (2) all towns without that type of physician will have a population smaller than that value. The empirical result is consistent with the model prediction even after relaxing some assumptions of the model. In another paper, they estimated a logit regression in which the dependent variable was whether a town had a given type of specialist in 1979 (Newhouse *et al*, 1982b). The results show that the linear population of town is always significant and the quadratic population term is significant in most cases and has a negative sign. Further analysis shows that after adjusting for border crossing by patient and controlling for changes over time in specialty composition, the regression result does not support the thesis that the market has failed.

Other research has looked at the location decision of individual physicians. Bolduc, Fortin and Fournier (1996) analyzed physician supply from individual physicians perspective. They used variables that measure marginal price of medical series, the regional rate of subsidy, virtual nonlabor-income, resources used to produce medical services, the supply of physicians in each specialty regional amenities and personal characteristics. They estimated a multinomial probit model and found that the average price elasticity of the supply of general practitioners in a region is 0.70 and the average income elasticity is 1.11. Their findings suggest that government policies that provide subsidies to physicians who work in underserved area will increase the supply of physicians of that area.

The central tenet motivating all this work is that the location decisions of physicians contribute to the community health. I am familiar with only one paper that actually attempts to determine the effect of physicians on community health. Miller, Dixon and Fendley (1986) used a human capital approach to examine the economic costs and benefits of adding medical manpower to rural and urban communities. Using mortality data, they constructed a monetarily based health index by applying prevailing average earnings to specific age and sex group to the productive time lost due to premature death. They included variables on the medical care sector such as number of hospital beds; hospitals and hospital expenditure in the model to control for the medical care system operating within the constraining context. Estimation results indicate that there are some states with negative marginal product of physicians in terms of the lost of human capital due to premature death. Some states have positive marginal product, which, however, cannot be justified by the marginal cost of physician. They conclude that beyond problems of misdistribution of physicians, the larger problem from an economic effectiveness perspective may be significant excesses of medical manpower.

There has been a wealth of research related to the central issue. Many papers have examined the effect of access and/or visits to an *individual's* health. As one example, McClellan, McNeil and Newhouse (1994) analyzed the effect of more intensive treatment of Acute Myocardial Infarction by using instrumental variables. They argue that patients who receive different treatments differ in observable and unobservable health characteristics, biasing estimates of treatment effects based on standard methods of adjusting for observable difference. They estimated incremental treatment effects using differential distances as instrumental variables to account for unobserved case-mix variation (selection bias) in observational Medicare claims data. They use Survival to 4 years after AMI (Acute Myocardial Infarction) as the main outcome measures. Comparisons of patient groups that differ only in differential distances show that the impact on mortality at 1 to 4 years after AMI of the incremental use of invasive procedure in Medicare patients was at most 5 percentage points. By using distance as the instrumental variables, they control for some unobserved characteristics and estimate the true effect of intensive treatment for AMI. The relevance to this study is an application of their finding. If distance to the nearest hospital with certain characteristics is correlated with the propensity of receiving catheterization, and catheterization increases survival probability, then distance to the nearest hospital with certain characteristics is correlated with survival probability. Applying this finding to physicians is the central focus of this paper.

Theory

Theory of individual health production function has been well developed (e.g. Grossman, 1972). In this paper, I will focus on community health instead of individual health. A community health production function can be written as:

$$Health = f(M, K, P, X, O)$$

Where M is number of MDs, K is capital put in health care such as hospitals. P is the population. X is the community characteristics. O is other factors that may affect the health. The hypotheses of interest is the first partial derivative of the health production function:

$$\frac{\partial Health}{\partial M} > 0$$

The first partial derivative of production function with respect to MDs is expected to have a positive sign, which indicates the positive marginal product of MDs. This is the focus of this paper.

The cross partial of health with respect to MDs and Population is hypothesized to be

$$\frac{\partial^2 Health}{\partial M \partial P} < 0$$

The negative sign of the cross partial indicates that the as the population grows, the effect of one MD on community's health is diminishing. This implies that the relationship between number of MDs in a community and health of that community is not linear.

Suppose that health is measured by the average health of 1000 people. One physician's effect on health will be manifested more in a smaller county than one with a larger population.

Empirical Model

The interest of this paper is to find out the effect of physicians on the health of the community in the sample. Suppose the population model is:

$$Health_{it} = \mathbf{a} * f(Mds_{it}) + \mathbf{b} X_{it} + u_i + e_{it}$$

Where $Health_{it}$ is the health is county i at period t, $f(Mds_{it})$ is a function of the number of MDs in county i at period t, X_{it} is other measured characteristics that has effect on health in county i at period t, u_i is an individual-level effect in county i that is persistent over time and e_{it} is a normally distributed error term with mean 0 and a constant variance $\mathbf{s}^2$. We initially assume

$$Cov(Mds_{it}, e_{it}) = 0$$
$$Cov(X_{it}, e_{it}) = 0$$
$$Cov(e_{it}, u_i) = 0$$

Individual-level effect u_i is the characteristic that affects health and may be correlated with number of MDs and does not change over time. This time-invariant effect may include things like underlying population norms and customs, distance to nearest medical school and hospital, and the geography of the county (such as mountainous terrain increasing travel times). However, we cannot observe u_i. If we omit u_i and only estimate the model:

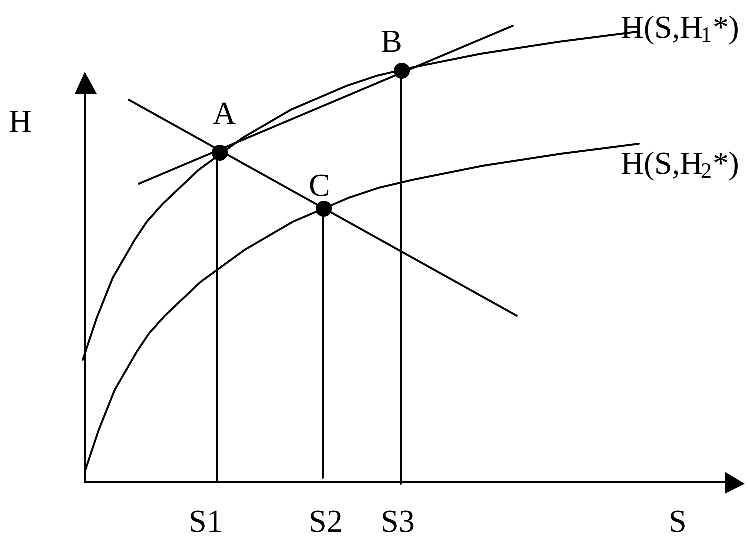
$$Health_{it} = \mathbf{a} * f(Mds_{it}) + \mathbf{b} X_{it} + w_{it}$$

The coefficient α will pick up some effect of u_i and leads to the biased estimation of α. Miller, Dixon and Fendley (1986) did cross section estimation and they included variables such as number of hospital beds, hospitals and hospital expenditure in the model to control for the medical care system operating within the community. They also included demographic variables such as nonwhite population, AFDC recipients, families in poverty, median education, occupation structure to control for sociodemographic structure of the community. These variables provide *some* indirect measurement of effect u_i. However, some community characteristics such as predisposal to MD visit and underlying health stock cannot be measured in variables above. So their models cannot estimate the effect of u_i which is in turn partially picked up by physician ratio variable. This leads the estimation of coefficient α to be biased. In this paper, the panel data model is used instead to control the unmeasured community characteristics that do not change over time:

$$Health_{it} = \beta_1 Mds_{it} + \beta_2 X_{it} + \beta_3 County_i + e_{it}$$

Where county is a 2375 x 1 column vector

In the panel model, county dummies pick up all the effect of u_i which is time invariant and not measured by variables *X*s. It corrects the biased OLS estimation. For example: suppose there are two county: $County_1$ and $County_2$. The health production function of $County_1$ is H(S,H_1*) and the health production function of $County_2$ is H(S,H_2*), where S is the physician supply and H* is the initial or latent health stock. Suppose $County_1$ has a better initial health situation than $County_2$ thus has a health production function above that of $County_2$'s. Now suppose the number of physician in $County_1$ is S_1 and the number of physician in $County_2$ is S_2. If we only estimate a cross sectional data, we are trying to explain the difference of health between $County_1$ and $County_2$ only by the difference in their physician supplies. So we are comparing point A and point C. This implies the result of increasing in supply of physicians, from S_1 toS_2, leading to decreasing in community health, from A to C. Thus, the OLS estimation would give us biased result of physician effect.



If we use panel data estimation to control for the community characteristics, the difference of initial health stock has been taken into account by applying fixed effect. In other words, the effect of u_i has been controlled. In this example, doing panel model enables us to explain the difference of health between $County_1$ and $County_2$ by both the difference in their physician supplies and the difference in their health situation. After controlling for initial health stock, we are comparing point A and point B. In this way, we will get an unbiased estimation of effect of physician on health, which is a better estimation than OLS.

Another potential econometric problem of the empirical model is heteroskedasticity. Low Disease Rate is used as the health index throughout this paper, which is computed as the ratio of number of death due to certain disease to population. It leads to the violation of the assumption that the variance of error term is constant. Assuming the probability of a disease in $county_i$ is p_i and the disease death in the county is independent from each other. Then, the total number of disease death has a binominal distribution with parameters p_i and n_i

$$disease_i \sim Bin(p_i, n_i)$$

Where p_i is the probability of disease death in $county_i$ and n_i is the population in $county_i$

The variance of total disease death is $n_i p_i (1 - p_i)$. And the variance of disease rate is

$$Var(disease\_rate_i) = Var(\frac{disease_i}{n_i}) = \frac{n_i p_i (1 - p_i)}{n_i^2} = \frac{p_i (1 - p_i)}{n_i}$$

So the variance of disease rate in is proportional to the population, which is not constant across the sample. To correct the heteroskedasticity, I use WLS to estimate the model with population as weight variable. The model estimation becomes:

$$disease\_rate_{it} * \sqrt{population_{it}} = \boldsymbol{b} X_{it} * \sqrt{population_{it}} + e_{it} * \sqrt{population_{it}}$$

Log form models are also estimated:

$$\log(Health_{it}) = \boldsymbol{b}_1 \log(Mds_{it}) + \boldsymbol{b}_2 \log(X_{it}) + \boldsymbol{b}_3 County_i + e_{it}$$

In log models, the coefficients can be interpreted as elasticity. For example, the coefficient of interest b_1 can be interpreted as the percentage change in health with one percentage increase in physician ratio. Besides, the variables' variation is reduced after taking the log form. This lessens the heteroskedasticity problem. In log models, robust standard errors (White, 1980) are estimated to correct the heteroskedasticity.

Heart Disease Rate, Influenza Rate and Mortality Rate are chosen to be dependent variables as the measure of health in empirical models. Physician variable is the ratio of physician to population instead of number of physicians. This is standard practice in this literature. Since one physician's effect on health will show up differently in different county with different population, which implies non-linear relationship between number of physicians and health, the physician ratio, is used in empirical model. Other controls in the model include Hospital, Hospital bed, Income, Poverty, Unemployment Rate and Black percentage

Data

The source of the data for this paper is from Area Resource File, Feb 1997. The file is published by Office of Research and Planning, Bureau of Health Professions. The data set includes detailed information about different years at county level.

Among all the variables, the variables Population, Low Birth Weight, Number of Ischemic Heart Disease, Number of Influenza & Pneumonia, Total Death, Number of Non Federal Mds, Number of Registered Nurse, Number of Physician Assistants, Number of Hospitals, Number of Hospital bed, Per Capita Income, Black Percentage, county code and state code are chosen for analysis. New variable Heart Disease Rate, Influenza Rate and Mortality Rate are created by dividing the corresponding values by population to measure the health of a given county. These three variables are chosen as the dependent variable to measure health situation in empirical models.

MDs ratio is created and its value is computed as the ratio of number of MDs to population in a given country. This is the independent variable of interest. Since the number of all physicians is not available in the data set, I use Non Federal Physicians as its proxy. Non Federal Physicians includes total active non-federal MDs in all categories.

Number of Registered Nurse and Number of African Americans have data only in 1980 and 1990. Linear interpolation is preformed to get the value between 1980 and 1988. Number of Hospital and number of hospital bed miss value in from 1981 to 1984. These values are also interpolated by a linear function. We include models both including and omitting these variables to examine robustness.

I limit my study to 2375 nonmetropolitan (rural) counties. The primary reason for this is that the county is being used as an approximation to a market. This approximation is likely less appropriate in urban counties.

The descriptive statistics is shown in table 1 and table 2. Based on the variable means, I plot mean MD Ratio, mean Mortality rate, mean Heart Disease rate and mean Influenza

Rate against year. The results are shown in graph one and graph two. Inspection of the two graphs shows that the mean Mortality Rate and mean Influenza Rate decreases over the decade and the mean Mds Ratios and mean Heart Disease Rate increase in the decade.

Results

The hypothesis of interest is that the number of physicians in a community improves the health in that community. I expect physicians improve community's health. Miller, Dixon and Fendley (1986) found positive marginal product of physicians in their paper. I estimated cross section model to test Miller, Dixon and Fendley's result. First, I did cross sectional estimation within one year (1988).

$$\log Health_i = \boldsymbol{b}_1 \log Mds_i + \boldsymbol{b}_2 \log X_i + e_i$$

The results are shown in Table 3. Heart disease rate, influenza rate and mortality are used respectively in the three models as the measure of health. Note that a lower value of dependent variables indicates better health situation. For example, a county with heart disease rate of 0.05 has a better health situation than a county with heart disease rate of 0.08. If the physician contribute to community health, the more physicians are in a county, the better health situation, thus the lower the value of disease rate and mortality rate. So the negative sign on the MD ratio variable implies positive marginal product of physicians. The coefficients on MD ratio variables have negative signs and significant at 1% level. The results thus serve to *qualitatively* replicate the central findings of Miller, Dixon, and Fendley.

Then I estimated physician effect using 8 years pooled (from 1980 to 1988) cross section data.

$$\log Health_{it} = \boldsymbol{b}_1 \log Mds_{it} + \boldsymbol{b}_2 \log X_{it} + \boldsymbol{b}_3 Year_t + e_{it}$$

The estimation results are shown in table 4. Again, the coefficients on MD ratio variables have negative sign and significant at 1% level. The cross sectional estimation result is consistent with Miller, Dixon and Fendley's. The results indicate positive physician marginal product.

Using fixed effect, a panel model is estimated to correct the omitting variables and some endogeneity effect:

$$LogHealth_{it} = \boldsymbol{b}_1 \log Mds_{it} + \boldsymbol{b}_2 \log X_{it} + \boldsymbol{b}_3 County_i + \boldsymbol{b}_4 year_t + e_{it}$$

Where county is a 2375 x 1 column vector

The results are shown in table 5. The coefficients on MD ratio become positive and significant in three models. The results indicate that the more physicians in a community, the worse health situation the community has. This, of course, is the opposite result as expected. We now explore different models to attempt to find the source of this aberration.

One-year lag of MD ratio is included in panel model, allowing the lag of Physicians' effect on health.

$$LogHealth_{it} = \boldsymbol{b}_1 \log Mds_{it-1} + \boldsymbol{b}_2 \log X_{it} + \boldsymbol{b}_3 County_i + \boldsymbol{b}_4 year_t + e_{it}$$

The estimation results are show in table 6. Coefficients on MD ratio are still positive. It's significant at 5% in mortality rate model and not significant at heart disease rate model and influenza rate model.

Based on the time trends exhibited in graphs 1 and 2, cointegration might be a problem. This would result in attributing the trend in the outcome variables to the trend in the ratio. I tried to correct it by estimating a panel model after first differencing dependent and independent variables. The results are shown in table 7, which does change a lot from the result of original panel model.

Endogeneity might be another problem. If physicians tend to locate in areas with higher disease rates, then reverse causation may be leading to biased coefficients. I tired to correct it by adding the lag of dependent variables as an instrumental variables in the model. The results are shown in table 8. The estimated coefficients are still opposite to what I expect and are different from Miller, Dixon and Fendley's results.

Estimation results of panel model using fixed effect are opposite to the result of cross section OLS models. Panel estimation result indicates negative relationship between MD ratio and the health situation. There are a couple of possibilities for this.

First, endogeneity could lead to the negative relationship. Poor health in a community may attract more physicians because there is more work to do. This leads to the phenomenon that a county has worse health situation would have more physicians.

Second, crowding out effect may also contribute to this negative relationship. Due to the limitation of the data, Non Federal MDs rather than All MDs is used to compute MD ratio. Poor health in a community will attract more Federal MDs, which may lead less to Non Federal MDs. Suppose there are 7 non federal physicians in a county. As the community health is getting worse, the government assigns 3 federal physicians to practice in the county. The increase in federal physicians supply crowd out non-federal physicians. 2 non-federal physicians leave the county. So the non-federal physicians decreases while total number of physicians increases. In this case, the relationship between health and Federal MDs is opposite to the relationship between Non Federal MDs. This would affect the sign of the coefficient estimation.

The third reason could be the lag problem. It's reasonable to assume that it takes some time for physicians to have an effect on community health. Though the lag of MD ratio is included in some models, the lag effect may not be correctly picked up by the lag variable.

Another problem may be a not well-defined market also affects the estimation result. The models are estimated on county level. It based on the assumption that the physician in one county will have effect only on that county's health. It ignores the possibility that individuals may travel to the nearby county to visit doctor. Of course, it's always possible that the true relationship between MD ratio and community health is zero or too small to be picked up.

Miller, Dixon and Fendley did OLS and they found positive marginal product of physicians. This paper uses fixed effect and has different result. Theoratically, fixed effect is better than OLS because it corrects the bias caused by omitted variables, which are time invariant. However, there are still some potentially problems for the fixed effect model. First, the model uses disease rate and mortality rate as dependent variable to measure the health. These variables provide some measurement for health but they are not perfect measurement. A particular disease rate may vary a lot from counties where the general underlying health situation may stay about the same. The mortality rate of a particular disease rate may correlate with a certain type of physicians and hospital equipment. Mortality rate is subject to many factors that are uncorrelated with health. So the future work should concentrate on developing a better measure of health. Hospital, Hospital bed, Income, Poverty, Unemployment Rate and Black Percentage are controlled in the models. However, there are still some factors that correlated with health and are time variant and not being picked up by fixed effect. More controls should be included in the model when data are available.

Conclusion

Miller, Dixon and Fendley (1986) found positive marginal product of physicians in their paper. I estimated cross section model to test the Miller, Dixon and Fendley's findings. The estimation coefficient on physician ratio has negative sign and is significant, which implies that physicians do contribute to population health. These results are consistent with that of Miller, Dixon and Fendley's. Fixed effect is used in panel data model to correct for the time invariant omitting variable bias. The coefficients on the physician ratio become positive and significant. Fixed effect model are estimated again only on rural area and the result remain the same, positive and significant coefficient on physician ratio. Including lag of Physician ratio doesn't change the results a lot. These findings are different from Miller, Dixon and Fendley's. Several possibilities were discussed in the paper including endognity, crowding out effect, lag effect, and non well-defined market.

There are a few potential problems with the model. Disease rate and mortality rate could not be a perfect measure of population health. A better health index should be developed in the future research work. Omitting variables that are time variant and correlate with dependent lead the estimation of physician effect to be biased. More controls should be included in the model when data are available in the future research work.

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Table 1

Descriptive Statistics

Physician Ratio

N=2375

Year	Mean	Standard Deviation
80	0.068665	0.05586
81	0.069817	0.0577
82	0.07047	0.05846
83	0.072189	0.059915
84	0.072861	0.061899
85	0.075467	0.064926
86	0.07545	0.065335
87	0.075983	0.065712
88	0.077255	0.066748

Table2

Descriptive Statistics

N=2375

Year	Mortality Rate		Influenza Rate		Heart Disease Rate	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
80	1.0182	0.2454	0.0337	0.0233	0.2900	0.1059
81	1.0080	0.2463	0.0343	0.0238	0.2824	0.1040
82	1.0000	0.2447	0.0304	0.0211	0.2796	0.1069
83	1.0155	0.2527	0.0345	0.0242	0.2774	0.1047
84	1.0115	0.2544	0.0347	0.0244	0.2692	0.1024
85	1.0259	0.2523	0.0401	0.0258	0.2652	0.1009
86	1.0297	0.2528	0.0403	0.0260	0.2557	0.0989
87	1.0321	0.2556	0.0390	0.0247	0.2525	0.0966
88	1.0571	0.2574	0.0450	0.0292	0.2529	0.0986

Table 3

One Year (1988) Cross Sectional Model

Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
log(MD to population Ratio)	-0.136**	-0.102**	-0.061**
	(0.028)	(0.039)	(0.018)
Income	-1.552	5.111**	0.065
	(0.817)	(1.221)	(0.611)
Poverty	-0.516	1.725**	0.260
	(0.354)	(0.360)	(0.189)
Nurse Ratio	0.318**	-0.053	0.148**
	(0.071)	(0.113)	(0.046)
Physician Assistant Ratio	-1.947**	0.155	-0.737
	(0.730)	(1.092)	(0.459)
Hospital	-0.035*	-0.034*	-0.029**
	(0.014)	(0.017)	(0.008)
Hospital Bed	0.273**	0.274	0.120
	(0.091)	(0.165)	(0.063)
Unemployment Rate	0.498	1.449	0.310
	(1.151)	(1.456)	(0.737)
Black Percentage	-0.199*	0.497**	0.044
	(0.098)	(0.116)	(0.052)
Observations	2233	1846	2236
R-squared	0.0796	0.0710	0.0458

Robust standard errors in parentheses

**: Significant at 1%; *: Significant at 5%

All regressions weighted by population.

Table 4

Pooled Cross Section Model

Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
log(MD to population Ratio)	-0.145 **	-0.054 **	-0.073 **
	(0.008)	(0.010)	(0.006)
Year	-0.021 **	0.031 **	-0.005 **
	(0.002)	(0.003)	(0.002)
Income	-0.126	1.237 **	1.155 **
	(0.328)	(0.342)	(0.230)
Poverty	-0.356 **	0.822 **	0.471 **
	(0.117)	(0.110)	(0.064)
Nurse Ratio	0.382 **	0.293 **	0.174 **
	(0.025)	(0.032)	(0.016)
Physician Assistant Ratio	-2.387 **	-1.149 **	-0.912 **
	(0.298)	(0.338)	(0.174)
Hospital	-0.027 **	-0.028 **	-0.019 **
	(0.004)	(0.005)	(0.003)
Hospital Bed	0.188 **	-0.016	0.080 **
	(0.026)	(0.023)	(0.017)
Unemployment Rate	1.199 **	-1.913 **	0.313 *
	(0.194)	(0.242)	(0.127)
Black Percentage	-0.189 **	-0.668 **	0.039 *
	(0.033)	(0.039)	(0.018)
Observations	20213	19131	20234
R-squared	0.1000	0.0866	0.0480

Robust standard errors in parentheses
**: Significant at 1%; *: Significant at 5%
All regressions weighted by population.

Table5

Fixed Effect Model

Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
log(MD to population Ratio)	0.019*	0.081**	0.023**
	(0.009)	(0.026)	(0.004)
Year	-0.016**	0.034**	0.004**
	(0.002)	(0.004)	(0.001)
Income	-0.565**	0.794	-0.019
	(0.200)	(0.507)	(0.096)
Poverty	0.217	1.803**	0.076
	(0.161)	(0.429)	(0.082)
Nurse Ratio	0.070*	0.130	0.065**
	(0.030)	(0.077)	(0.013)
Physician Assistant Ratio	-0.479*	0.787	0.029
	(0.236)	(0.592)	(0.105)
Hospital	-0.001	0.011	-0.004
	(0.006)	(0.016)	(0.003)
Hospital Bed	0.015	-0.045	0.048*
	(0.044)	(0.106)	(0.023)
Unemployment Rate	-0.232*	-2.633**	-0.537**
	(0.097)	(0.277)	(0.051)
Black Percentage	0.304	-0.222	0.581**
	(0.412)	(1.142)	(0.189)
Observations	20213	19131	20234
R-squared	0.8477	0.4999	0.9112

Robust standard errors in parentheses
**: Significant at 1%; *: Significant at 5%
All regressions weighted by population.

Table 6

Fixed Effect: lag of MD

Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
One year lag of log MD Ratio	0.00365	0.04156	0.01428 **
	0.01018	0.02827	0.00469
Year	-0.016 **	0.036 **	0.004 **
	(0.002)	(0.004)	(0.001)
Income	-0.608 **	1.491 **	0.045
	(0.216)	(0.552)	(0.106)
Poverty	0.477 *	2.068 **	0.135
	(0.190)	(0.513)	(0.092)
Nurse Ratio	0.054	0.153	0.074 **
	(0.035)	(0.093)	(0.016)
Physician Assistant Ratio	-0.384	1.508 *	0.115
	(0.286)	(0.712)	(0.123)
Hospital	0.001	0.000	-0.006
	(0.007)	(0.018)	(0.003)
Hospital Bed	0.010	-0.037	0.037
	(0.046)	(0.110)	(0.021)
Unemployment Rate	-0.284 **	-1.915 **	-0.359 **
	(0.110)	(0.309)	(0.058)
Black Percentage	0.105	0.891	0.766 **
	(0.495)	(1.383)	(0.215)
Observations	17981	17037	17997
R-squared	0.8527	0.5125	0.9157

Robust standard errors in parentheses
**: Significant at 1%; *: Significant at 5%
All regressions weighted by population.

Table 7

Cointegration Model

Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
Difference of log MD Ratio	0.024	0.117**	0.028**
	(0.014)	(0.043)	(0.007)
Year	0.003**	0.016**	0.004**
	(0.001)	(0.003)	(0.001)
Income	-0.355**	0.053	-0.169**
	(0.117)	(0.334)	(0.059)
Poverty	-0.051	-0.091	-0.030
	(0.041)	(0.112)	(0.019)
Nurse Ratio	0.004	-0.011	0.007
	(0.011)	(0.032)	(0.005)
Physician Assistant Ratio	0.044	-0.064	-0.009
	(0.137)	(0.376)	(0.061)
Hospital	0.001	0.000	-0.001
	(0.002)	(0.005)	(0.001)
Hospital Bed	0.001	0.016	0.003
	(0.008)	(0.027)	(0.004)
Unemployment Rate	0.132	0.620*	0.161**
	(0.087)	(0.281)	(0.047)
Black Percentage	0.005	0.020	-0.001
	(0.015)	(0.042)	(0.007)
Observations	17868	16284	17898
R-squared	0.0013	0.0042	0.0076

Robust standard errors in parentheses
**: Significant at 1%; *: Significant at 5%
All regressions weighted by population.

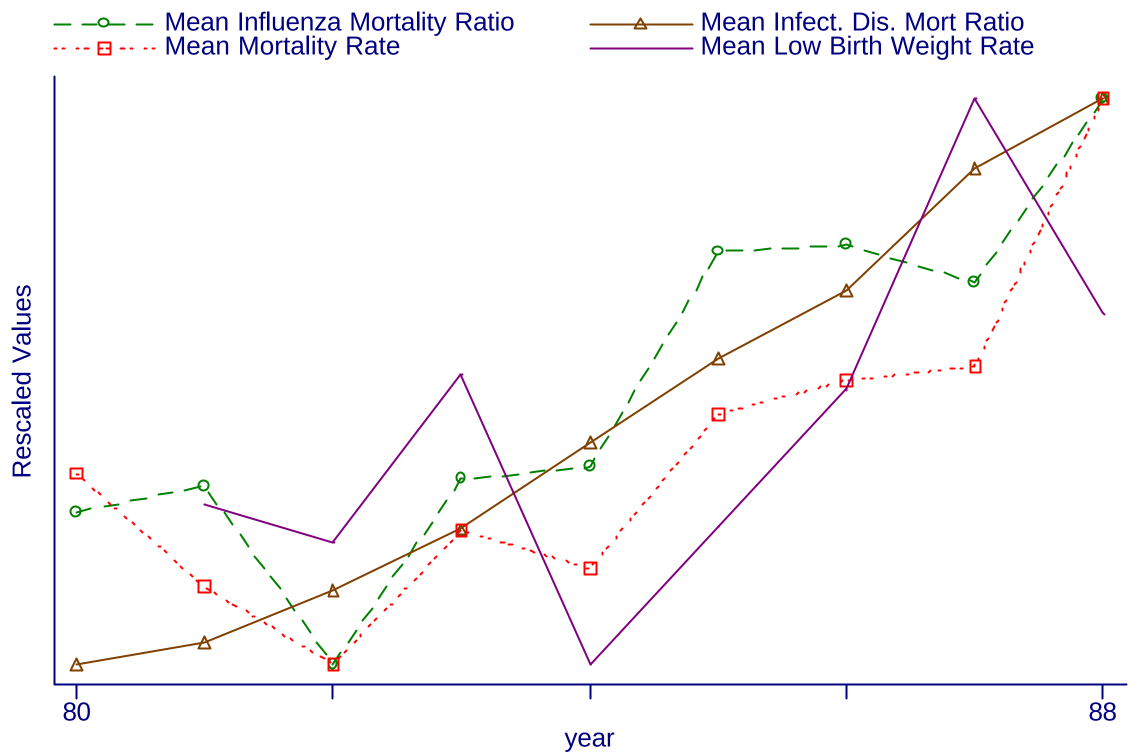
Table 8

Instrumental Variable Model

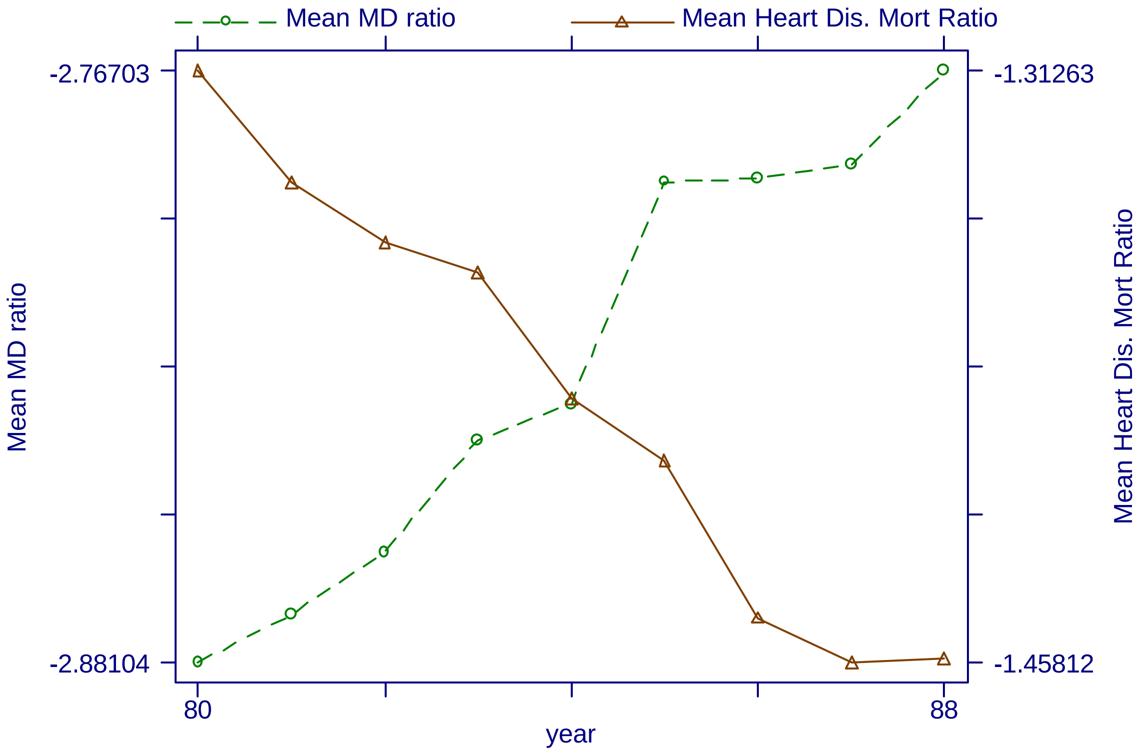
Variable	Models		
	Heart Disease Rate	Influenza Rate	Morality Rate
Log MD Ratio	-0.015	-0.070 *	0.000
	(0.010)	(0.035)	(0.005)
Income	-0.649 *	4.182 **	-0.129
	(0.302)	(1.082)	(0.135)
Poverty	-0.014	1.183 **	0.044
	(0.123)	(0.354)	(0.054)
Nurse Ratio	0.028	-0.057	0.010
	(0.033)	(0.108)	(0.015)
Physician Assistant Ratio	-0.600	0.589	-0.342 *
	(0.357)	(1.209)	(0.152)
Hospital	-0.007	-0.018	-0.004
	(0.005)	(0.016)	(0.003)
Hospital Bed	0.055 *	0.193	0.009
	(0.027)	(0.136)	(0.014)
Unemployment Rate	-0.060	2.004	0.304
	(0.518)	(1.467)	(0.203)
Black Percentage	-0.068	0.420 **	-0.005
	(0.041)	(0.115)	(0.017)
Lag of Mortality Rate			0.912 **
			(0.010)
Lag of Influenza Rate		0.250 **	
		(0.030)	
Lag of Hear Disease Rate	0.841 **		
	(0.017)		
Observations	2232	1586	2236
R-squared	0.7306	0.1314	0.8423

Robust standard errors in parentheses
**: Significant at 1%; *: Significant at 5%
All regressions weighted by population.

Graph one


Mean Influenza Mortality Ratio
Mean Infect. Dis. Mort Ratio
Mean Mortality Rate
Mean Low Birth Weight Rate
Rescaled Values
80
88
year

Graph Two


Mean MD ratio
Mean Heart Dis. Mort Ratio
-2.76703
-2.88104
-1.31263
-1.45812
Mean MD ratio
Mean Heart Dis. Mort Ratio
80
88
year