Do more doctors make us better off?

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November, 15 2006

Abstract

Previous studies report conflicting results about the effect of physician density on health outcomes. In this paper I construct a unique panel dataset and use a region fixed effects and instrumental variable strategy to examine the relationship between physician density and population health outcomes in more detail. The results suggest that unobserved heterogeneity and endogeneity between my measures of population health and physician density is present. I conclude that this evidence does not support the claim that an increase in physician density would increase population health in the U.S.

JEL classification: I18, R38

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I. Introduction

In 2005, the American Medical Association (AMA) declared a shortage of physicians in the U.S. (AMA 2005). Reacting to this, by June of the following year, the Association of American Medical Colleges (AAMC), which controls the number of medical students being enrolled in U.S. medical schools each year, called for a 30 percent increase in enrollment by 2015 (AAMC 2006). An increase of 30 percent in medical school enrollment would increase tuition related income of medical schools by a sizeable amount, perhaps accounting for this recommendation. Whether the U.S. really needs more physicians is hotly debated among medical practitioners, health policy researchers, legislators, and health economists. Those who plead for more physicians generally attribute the increasing demand for physicians to a steady and continuous growth in a country's ageing population. But do more physicians necessarily improve the population's health?

It is possible that an increase in the supply of physicians has little or no effect on population health, and instead simply increases the demand for physician services. To what extent physicians can really induce demand has been debated by experts for decades (see for example, Reinhardt 1985; Phelps 1986; Feldman 1988; Rice 1989; Sorensen and Grytten 1999; Xirasagar and Lin 2006). If such an effect is present in the U.S., more physicians would raise health care expenditures in an economy where spending on health care is already the highest (in terms of percent of GDP and per person) without an effect on health outcomes (Heffler et al., 2005). Therefore, it is absolutely crucial to inquire if increasing the number of physicians per person will result in better health care for the population being served. Steps to increase the physician supply should only be taken if the inquiry leads to positive results with clear and convincing evidence.

Until now, previous studies that link higher physician density to better health outcomes and consumer satisfaction did not explore the possible endogeneity of health and physician density. In this paper, I test for possible endogeneity, as well as unobserved heterogeneity, between health indicators and physician density. Health outcomes and the number of physicians in any given region can be inter-related in three different ways:

1. Physician density affects health. For example, more physicians per person means each physician gets more time to diagnose and treat a patient, which in turn leads to better health outcomes for the population as a whole.
2. Health affects physician density. Given that illness creates demand for health services, physicians tend to concentrate more in areas where more sick people are located than elsewhere.
3. Unobserved variables influence both health and physician density.

In this paper, I use ordinary least squares (OLS), an area fixed effect model and an instrumental variable approach to determine which of these three explanations is responsible for the correlation between physician density and health outcomes demonstrated by previous studies (Shipp et al. 2005, Fan et al. 2006). I conclude that an increase in physician density may not necessarily result in improving the health of the population in that area. The remainder of the paper is structured as follows: Section II discusses previous studies; Section III describes the data used in this analysis and Section IV the estimation methods; Section V presents empirical results and Section VI concludes.

II. Previous Studies

Shipp et al. (2005) study colon cancer incidence rates in Alabama counties in relation to socioeconomic variables and physician density. They observe a positive and statistically significant relationship between physician density and colon cancer incidence rates in Alabama.

Fan et al. (2006) carry out similar studies on end-stage renal disease in South Carolina counties. In addition to using standard socioeconomic control variables, they also include a dichotomous variable indicating whether a county is urban or rural. They find that higher physician density is associated with a lower risk of developing end-stage renal disease.

The effects of physician density in those two studies are the exact opposite of each other. This outcome might be due to measurement error introduced by not fully appreciating the difference between physician density and actual access to care. Newhouse (1990) and Rosenthal, Zaslavsky, and Newhouse (2005) show that in rural counties with low physician density, but in close proximity to an urban county with high physician density, access to medical care is not necessarily worse. The population in the rural county will access the physicians in the urban county and receive the same health benefits as the urban population. This introduces measurement error, which can lead to bias in the estimated coefficient for physician density. This bias along with differences in their sample data might be the reason for the different results of Fan et al. (2006) and Shipp et al. (2005).

To account for the possibility of measurement error at the county level, the variables for this study are measured at the level of the Metropolitan Statistical Area (MSA), which is much broader than the county level. Cross boarder access to care is much less likely to occur as MSAs are rarely adjacent to each other.

Second, I consider that health outcomes and physician density might be related to each other in more ways than one. It is possible that the average health of the population in a region influences the location choice of physicians. A medical practitioner might consider locating in an area with a sicker population, as this signals higher demand for his services. It is also possible that unobserved variables affect the location choice of both physicians and of populations of a certain health. For instance, the location preference of physicians may be the same as that of healthy individuals.

To understand the effect of physician density on population health, I construct a new panel data set at the MSA level. This allows me to run an MSA fixed effects model to control for unobserved heterogeneity in physician density. I also consider an instrumental variable approach to address the reverse causality that may be present in the relation between physician density and population health.

III. Data used in this analysis

The data used in the statistical analysis of this paper comes from the Census' *County Business Patterns* (CBP), the Centers for Disease Control and Prevention's (CDC) *Behavioral Risk Factor Surveillance System* (BRFSS), the *National Vital Statistics System* (NVSS) of the National Center for Health Statistics, and the *National Practitioner Data Bank* (NPDB) of the Health Resources and Services Administration. Data on MSA size and population numbers come from the Census. The CBP have been published annually since 1964. Since 1998, the data are tabulated based on the North American Industry

Classification System (NAICS). The CBP give detailed information, by NAICS codes, about the number of employees, payroll, the total number of establishments, and the number of establishments under different categories of employment size, in each county. The series excludes data on self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees.

The CBP data is compiled for the years from 1998 to 2002. The comparability of data over time may be affected by definitional changes in establishments, activity status, and industrial classifications. To safeguard against this possibility and to keep the data as comparable as possible the analysis of this paper is done from 1998 onwards. This way I avoid possible, problems of comparing data from two different industrial classification systems, since data for 1997 and earlier years are based on the Standard Industrial Classification (SIC) System.

The second set of data used in this paper comes from the BRFSS. Five years of data from 1998 to 2002 are used by pooling the individual years into one dataset. For all these years, data is available for all the 50 states and the District of Columbia. Since 1981, the CDC has been collaborating with state health departments in collecting this data annually, to track health behaviors related to premature causes of death. Initially, only 15 states participated in monthly data collection, but from 1994 onwards, all states, including the District of Columbia, participated in the survey (CDC 2002). The survey is designed to be representative by state and is stratified by age, sex, and race.

The BRFSS data was chosen because of its distinct advantages. It has a large sample size, an extensive and consistent questionnaire about individual characteristics and health behavior, offers consistent cross-sections for all five years, and includes county identifiers.

The main disadvantage is that the BRFSS is not a panel survey; and as a result, individual decisions about location choice based on health care services cannot be investigated.

The BRFSS only supplies county codes if more than 50 people of the respective county participated in their survey that year. That means I have had to exclude approximately 22 percent of the BRFSS data due to missing county identifiers. Each county, in both the BRFSS and the CBP, is then associated with the correct MSA area as specified by the National Institute of Standards and Technology. After merging the two datasets, I am left with 530,378 individual observations for 251 individual MSAs or 995 MSAs for the 5-year period of my data. Most MSAs are not observed for all of the 5 years. The average number of years a MSA is observed in my data is 4 years.

Data from the NVSS, NPDB, and MSA area and population size from the Census is then merged with this data and aggregated at the MSA level. This leaves me with an unbalanced panel for the years 1998 to 2002. This data is not representative of the whole United States, but should be a good indicator of the urban population, which constitutes about 80 percent of U.S. population. The average population density in the MSAs of my data is 506 people per square mile. The MSA with the lowest population density is Casper, Wyoming with an average of 12.5 people per square mile over the years 1998 to 2002. The highest population density is in Jersey City, New Jersey with an average of 12,996.5 people per square mile. While it is unfortunate that these data are not able to say much about the effects of physician density on populations in a rural setting, obtaining results for more metropolitan areas is still important.

My two dependent variables are the aggregation of self-rated health and the incidence of diabetes in a MSA. The variable diabetes excludes gestational diabetes. At the individual level, *Health* can take on three values: poor to fair, good, and very good to excellent. This is derived from a self-assessment of health that can take on five different values: excellent health, very good health, good health, fair health, and poor health. The values for excellent and very good health and those for fair and poor health are combined into one category each. This is commonly done to compensate for overly enthusiastic and overly pessimistic individuals[2]. Self-rated health and diabetes were chosen as the two dependent variables since they represent a general as well as a more concrete measure of population health. Unfortunately, data on the health measures, namely colon cancer rates and the incidence of end stage renal disease, covered by the two previous studies, was not included in the BRFSS data.

Diabetes is a specific health outcome. When recognized early enough, individuals at the risk of developing diabetes can take steps and be treated so that they will not develop full blown diabetes. If, other things being equal, a higher physician density does indeed have an effect on health outcomes, this should be directly reflected in the diabetes incidence rate of a population.

Self-rated health, on the other hand, gives a more general indication about the health status of a population. If a higher physician density affects certain health outcomes, this should be reflected in the general health of a population. Higher physician density, notwithstanding its effect on other health outcomes, may not have any effect on diabetes rates. In this case the effect on other health outcomes should still permeate into the general health of a population. Let's say more physicians in an area means that the population in this area will have fewer cancer incidents or that cancer will be recognized much earlier and

[2] However, the results presented in this paper hold also true if all 5 categories of self-rated health are used in the regressions.

treated better than in areas with fewer physicians per person. Other things being equal, this should be reflected in the general health of the population, because people with fewer cancer rates and/or better cancer treatment should feel healthier than a population with more cancer rates and/or worse treatment.

The main explanatory variable of interest in this study is physician density. Unfortunately, I do not have data on the number of physicians in a MSA as did other researchers. For this paper, I approximate physician density based on the number of employees in physician offices in each MSA per 10 people. The number of employees in physician offices is derived from the 5 digit NACIS code 621111 in the CBP, defined as "Offices of Physicians (except Mental Health Specialists)". While it might not be a perfect measure of true physician density, the number of employees in a physician office is highly correlated to the actual number of physicians. One advantage of using physician office employees, instead of actual physician numbers, is that it might pick up productivity differences. A physician who only works part time or does not see many patients in a day might employ only 1 or 2 people, while a physician who sees many patients per day and has an extensive practice network might employ many more people. Using raw physician numbers per MSA will not pick up this difference in productivity while the number of employees is a better approximation of real productivity per physician. Chart 1 shows the development of my measure of physician density over the time period of this analysis in the U.S. and selected MSAs. For the U.S. as a whole, physician density is slowly increasing. In New York, physician density seems to be relatively stable, and it decreases in Orange County.

Table 1 shows the sampled means of my data for the variables of interest. As all data is aggregated at the MSA level, variables that were binary for individuals now represent the percentage of the population in the respective category. It is interesting that the average Body Mass Index (BMI) has almost reached 30, the threshold value for obesity, as defined by the WHO. Research density is defined as the number of scientific research institutions per 1000 people in a MSA. Birth rate is the number of newborns per 1000 people in a MSA and malpractice payments is the Dollar amount of malpractice payments per employee in physician's offices in the state. The variable malpractice payments consist of money paid from any malpractice payments from insurers, medical practitioners, hospitals, professional societies, or other entities and includes money paid due to litigation from in and out of court settlements. Any payment made due to malpractice is required to be reported by those entities as are required under the provisions of Title IV of P.L. 99-660, the Health Care Quality Improvement Act of 1986. The highest malpractice payment was in New York in 2001 with $6,055 per employee and the lowest was in Indiana in 2002 with $331 per employee.

Some people may argue that there is not enough variation in the variable that measures physician density. In general, a variable that exhibits no or only very little variation between the units of interest or within each unit over time, might not be a good explanatory variable. To assess if there is variation in physician density, I compute the *between* and *within* variations, as well as their respective minimum and maximum. The *between* variation is a measure of the difference in the time averages of a variable between MSA regions in the data. The *between* standard deviation will be very small or 0 if the difference in a variable between MSA regions is little or nil. With 2.160, Kileen-Temple, TX had the smallest average of physician density over the 5-year period and Elkhart-Goshen, IN the highest with 30.858. The *between* standard deviation for physician density is 2.472 which is calculated over the 251 individual MSAs in the data.

Similarly, the *within* variation is a measure of the difference within the variable of interest in each MSA over time. If a variable does not vary over time, its *within* variation is zero. The concern here is that if an explanatory variable is time-invariant within each MSA, it should not be used to estimate an effect on the dependent variable in a panel data model, such as fixed effects. For the *within* variation, the minimum and maximum refer to the deviations from each MSA's average. The *within* minimum and maximum for physician density are 3.156 and 12.146 respectively. The *within* variation observed over the 5-year period of my data within a MSA is 0.603, which is calculated over the 985 MSA-years of data. The *within* variation is smaller than the normal or *between* variation of physician density, but is still almost 10 percent of the mean. There doesn't seem to be any indication that the variation of physician density should be a cause of concern due to insufficient variation between or within MSAs. The other variables used in the analysis also exhibit *between* and *within* variations. All of them are several percent of their respective mean.

IV. Estimation Strategy

I first estimate two separate ordinary least squares models for the two dependent variables, *Health* and *Diabetes*, treating physician density as a dependent variable along with other socioeconomic variables described in Table 1. The first set of estimations is at the MSA level and the second at the county level. According to Newhouse (1990) and Rosenthal, Zaslavsky, and Newhouse (2005), the difference between a county level and a

MSA level analysis, using the proposed covariates, should be mainly in the variable physician density, as it doesn't pick up actual access to care in a county.

To account for unobserved time-invariant location specific effects in the estimated equations, I also consider an MSA fixed effects model. Let PD_{it} denote the number of employees in physicians offices in MSA i at time t, $Health_{it}$ the MSA average of self-rated health or the incidence of diabetes in MSA i at time t, X_{it} a vector of population characteristics for each MSA i at time t, c_i the unobserved component, and u_{it} the idiosyncratic disturbances. Then, the unobserved effects model can be expressed as follows:

$$Health_{it} = \gamma PD_{it} + \beta X_{it} + c_i + u_{it}, \qquad t = 1,2,\ldots,5;\ i = 1,2,\ldots,251 \tag{1}$$

By including MSA fixed effects in equation (1), we effectively control for any unobserved time-invariant component that might be correlated with *Health* and *Physician Density.* The vector X contains information about population age, sex, race, education, income, and health indicators such as the percentage of people actively smoking in each MSA, the percentage of people covered by health insurance, and the average Body Mass Index (BMI) expressed in terms of weight in kilograms over the height in meters squared. A person with a BMI over 25 is considered overweight and a person with a BMI over 30 is considered obese. The recent increase in overweight and obesity is regarded as a major health threat to the U.S. population (Mokdad et. al, 2004).

Even after controlling for unobserved time-invariant effects, simultaneity bias due to possible endogeneity of *Physician Density* may be present. To offset this possibility, I employ an instrumental variable approach. Let I_{it} be the set of instruments in MSA i at time t, and e_{it} and u_{it} the respective residuals. Then the two stage process can be expressed as follows:

$$Health_{it} = \gamma PD_{it} + \beta X_{it} + u_{it,} \qquad t = 1,2,\ldots,5;\ i = 1,2,\ldots,251 \qquad (2)$$

$$PD_{it} = \delta I_{it} + \zeta X_{it} + e_{it} \qquad t = 1,2,\ldots,5;\ i = 1,2,\ldots,251 \qquad (3)$$

The instruments for physician density are scientific research institutions per 1000 people, births per 1000 people, and the amount of money awarded in malpractice suits per physician office employee. Identification rests on two assumptions, namely (i) that each instrument is correlated with physician density and (ii) uncorrelated with the health residual. Many physicians prefer to continue their research even as they work, and thus a higher concentration of scientific research institutions can be an incentive for physicians in choosing their area of service. Such physicians are either directly associated with those research institutions or are indirectly affiliated with them. If research institutions attract in general more educated people, their concentration might also be correlated with the health residual if education is not controlled for. I include several controls for education which take care of this possibility. Pregnancy and child birth are associated with demand for physician services. A higher birth rate should, therefore, be correlated with higher physician density. The birth rate can be correlated with the health residual since a younger and healthy population gives more births than an older and less healthy population. The control for age should compensate for this possibility. A high malpractice payout signals a locality where the risk of malpractice lawsuits is high. Therefore, the amount of malpractice payments per employee in physician offices should be negatively associated with physician density on the assumption that physicians dislike a higher risk of malpractice lawsuits. It is not clear how this variable could be correlated with population health.

V. Results

Table 2 presents the OLS results for the average self-rated health and diabetes incidence rate in each MSA. All variables have the expected signs and most are highly significant. Physician density is positively associated with higher average self-rated health in a MSA and negatively associated with the average diabetes incidence rate in that MSA. For self-rated health, the coefficient of the variable physician density is significant at the 1 percent level and for diabetes it is significant at the 5 percent level. A higher percentage of females in an MSA is associated with lower health. Higher percentages of younger age groups in an MSA are positively associated with better health, except for the age group of 45 to 64 year olds, whose health is not statistically different from that of over 65 year olds. Compared to a Caucasian population, a higher percentage of both African-American and Hispanic populations are associated with lower health. A larger percentage of people with higher income and higher education is related to higher self-rated health of a population in a MSA. Both higher smoking rates and higher BMI are associated with lower health. Somewhat surprisingly an MSA with a higher percentage of HMOs operating within its borders has better health. The stigma that patients' health gets sacrificed due to the different operating structure of HMOs does not seem to be true.

For diabetes, most results are also as expected. Increasing age, as well as a larger percentage of African-Americans, is related to higher diabetes rates in a MSA, except for the youngest age group of 18-29 year olds, which is not statistically different from over 65 year olds. A population with a higher percentage of people in higher income categories is associated with lower diabetes rates, as is a population with more education. It is well documented that obesity is a major risk factor for type 2 diabetes, and hence it is not surprising that a higher average BMI in an MSA is positively associated with a higher diabetes rate. The only surprising coefficient is the positive association of healthcare coverage with diabetes at a 10 percent significance level. This might indicate that people without health care coverage will not consult a doctor as often as they need to and thus will not be able to detect when they enter a pre-diabetic state.

The estimations in Table 2 assume that self-rated health and diabetes rates are linear in physician density. To test this assumption, I perform a Ramsey RESET test for linearity (Thursby and Schmidt 1977). The F statistic for self-rated health equation is 3.06, which is associated with a p-value of 0.081. That means we can reject the hypothesis of linearity of self-rated health in physician density at the 10 percent level, but not at the 5 percent level. The F statistic for diabetes equation is 1.23, which is associated with a p-value of 0.268. That means we cannot reject the hypothesis of linearity of diabetes in physician density. As there seems to be some evidence that self-rated health and diabetes might be non-linear in physician density, I re-estimate the two equations with the log of physician density. This did not lead to any change in the sign and statistical significance for physician density on self-rated health and diabetes. The coefficient for the log of physician density on self-rated health and its standard error is 0.021 and 0.007 respectively; for diabetes, the corresponding figures are -0.0036 and 0.002.

To show the difference in the estimation of the effects of physician health between county and MSA level analyses, I also estimate the OLS regressions for self-rated health and diabetes at the county level. Table 3 presents the county level results. Except for physician density, all other covariates exhibit similar magnitude, sign, and statistical significance as in the MSA results. At the county level, higher physician density is significantly associated with lower population health and positively with diabetes rates. As explained above, the county level regressions are most likely biased due to measurement error. Further analysis of the effects of physician density on population health and disease incidents is therefore done at the broader MSA level to avoid possible measurement error in health care access.

While the covariates used in this analysis all have strong explanatory power, it is possible that there are unobserved factors that affect both physician density and population health. In this case, OLS estimation will be biased and the coefficients on physician density are misleading. Anecdotal evidence suggests that the location choice of physicians might generally be similar to that of health-conscious individuals. While it is not possible to test for the presence of unobserved heterogeneity I can exploit the panel structure of my data to eliminate location specific fixed effect. To see whether time-invariant heterogeneity is present, I run an MSA fixed effects model on the average self-rated health and diabetes rate in a MSA.

Table 4 lists the results of the fixed effects model for self-rated health and diabetes rate. The physician density coefficients in both, the self-rated health and diabetes equations, become statistically insignificant. This suggests that the positive correlation between physician density and the average self-rated health and between physician density and the diabetes rate of a population are due to time-invariant heterogeneity. Once those unobserved effects are controlled, the correlations between physician density and my health measures become less precise[3].

The results for the other variables are relatively robust. The negative association between a larger female population and lower self-rated health is not significant anymore. The coefficients for the smoking rate and the percentage of HMO coverage also loose their significance on self-rated health in a MSA. For the diabetes rate in a MSA, the results are similar. The race effects become statistically insignificant. Only a higher percentage of individuals with high school degree compared to less than high school degree is still associated with lower rates of diabetes. The surprisingly positive effect of health care coverage on diabetes rates also disappears.

As linearity of self-rate health in physician density was rejected at the 5 percent level, I run both, self-rated health and diabetes, with MSA fixed effects and the log of physician density. The sign for physician density on the average self-rated health and diabetes rates in a MSA does not change and is still statistically insignificant. The coefficient for the log of physician density on self-rated health and its standard error is -0.008 and 0.028 respectively; the corresponding figures for diabetes rates are -0.001 and 0.010.

The fixed effects model suggests that time-invariant heterogeneity is a cause of the correlation of physician density on both the average self-rated health and diabetes rate in a MSA. But it is possible that some unobserved factors, which vary over time, affect physician density and the average self-rated health and diabetes rate in a MSA. To rule out this

[3] One concern of the model that is estimated here is that other variables beside physician density are potentially endogenous in health. The health of an individual might influence the decision to smoke, have an effect on weight, and whether or not an individual is able to take up health insurance. Health might also affect earnings and the ability to reach a certain educational category. To see if the qualitative results are stable I estimate OLS and MSA fixed effects models including only the strictly exogenous variables age, sex, race, and year effects plus physician density. While the magnitude of the coefficients change somewhat, the sign and significance of the variables is preserved. Physician density becomes significant at the 1 percent level for both self-rated health and diabetes in the OLS regressions and is non-significant for both equations in the fixed effects models.

possibility, an instrumental variable approach is considered. In this paper, I use scientific research institutions per 1000 people, births per 1000 people, and the amount of money awarded in malpractice suits per physician office employee. A Hansen-Sargan test of the null hypothesis that the excluded instruments are uncorrelated with the error term and correctly excluded from equation (2) as suggested by Sargan (1958) cannot be rejected with a p-value of 0.336.

The results of the first stage in the instrumental variable regression are listed in table 5. All three instruments have the expected signs, and the birth rate and malpractice variable are statistically significant at the 1 percent level. The number of research institutions per 1000 people, however, is not statistically significant. Most other covariates have the expected sign. The only surprising results are the income categories. These results show that the higher the percentage of the population in higher income categories, the lower would be the physician density. On the other hand, a more educated population attracts more physicians. As expected, a higher percentage of HMOs in a MSA results in lower physician density. The F-statistic of the reduced form first stage, for the hypothesis that all coefficients jointly equal zero, is 14.1. This figure is above the minimum F-statistic of 10 that is suggested as a test for weak instruments with one endogenous variable by Staiger and Stock (1997).

Table 6 lists the results of the instrumental variable regressions on the average self-rated health and diabetes rate in an MSA. Just as in the fixed effects model, both of the coefficients for physician density are statistically insignificant[4]. Compared to the OLS estimates, the other regressors for both equations are very similar. The magnitude of some

[4] The results hold for all combinations of the three presented instruments. Research density by itself, however, is a weak instrument with a reduced form first-stage F-statistic of 1.56.

coefficients changes minimally. A Hausman test of the hypothesis that OLS and IV coefficients are equal is rejected for both, the self-rated health and diabetes equation. This suggests that health outcomes and physician density are indeed endogenous and that time-invariant as well as time-variant heterogeneity may affect physician density.

In the next step, I run the instrumental variable equations with first differences to control both time-variant and time-invariant heterogeneity. The decision of physicians to locate themselves in a specific region might depend on previous' years observations in that region and thus introduce autocorrelation into the error terms. If this is the case, a first differencing approach can control for it, as described in Wooldridge (2002). The results are listed in Table 7. Again, the coefficients for physician density on the average self-rated health and diabetes rate in a MSA are statistically not significant. All the other covariates, considering all estimation methods, are surprisingly robust. The first stage for the first differencing estimation is listed in table 8. Only the variable 'malpractice payments' is still significant at the 10 percent level. All other covariates, except health insurance coverage, are not statistically significant anymore. With an F-statistic of 0.73 my instruments are also considered weak instruments in the first differenced instrumental variable estimation.

It is thought that the location of medical practitioners as well as the health of individuals is highly dependent on income and education. To account for the interdependences between those variable I estimate a model that includes interaction terms of physician density and the income and education categories. Table 9 lists the coefficients for physician density and the included interaction terms for the OLS, fixed effects, and the IV models. In the OLS model for self-rated health, the coefficients for physician density as well as for the interactions with the first 3 income categories are positive and statistically significant. However, none of the coefficients in the diabetes equation is statistically significant. The fixed effects model seems to suggest that the interactions with the educational categories are more relevant than the income interactions or physician density by itself. When physician density is instrumented, all of the interaction terms become statistically insignificant.

VI. Conclusion

This paper finds no convincing evidence that physician density significantly affects population health. Previous studies that use counties as the geographical unit of analysis report conflicting results for the relationship of physician density and health outcomes. Previous research that is supported by my county level estimations suggests that a broader geographic level of analysis will be less prone to measurement error due to county border crossing. Therefore, this paper uses MSAs as the geographical unit of analysis. Additionally, previous researchers did not consider, owing mainly to data limitations, the possible endogeneity of physician density. To improve on previous research I also use several years of health outcomes and physician density data in my investigation. The data sources used in this analysis allow me to construct a unique panel dataset. This panel structure of my data enables me to use an MSA fixed effects approach to control for the possibility of unobserved heterogeneity of physician density. Additionally I consider the number of scientific research institutions per 1000 persons, the local birth rate, and the amount of money awarded in malpractice suits per physician office employee as instruments for physician density.

This paper has several limitations, however. First, my measure of physician density is not the same as that of other papers. I use the number of employees in physician offices as an approximation to physician density. This measure is highly correlated with physician density, and arguments can be made that the number of employees in a physician office represents physician productivity more accurately than raw physician numbers. Second, the health outcomes I use are also not the same as those used by previous studies. I use a very general health measure and a more specific one to show that my results are robust in both cases, but this is not absolute evidence that physician density might not have an impact on other health measures. Third, while there are convincing arguments that the instruments are not correlated with the error term of the second stage estimation, it is not possible to statistically test this hypothesis. Fourth, like in previous studies, physician density is not the same as actual access to care. Health care access can be delivered through many mechanisms such as physicians' offices, hospitals, and managed care organizations. It is possible that the number of physicians is an inadequate measure of actual access to care. In this case both previous results and mine might exhibit measurement error. On the other hand, if physician density is not an adequate measure of health care access, than increasing the number of physicians in the U.S. will not necessarily lead to better access to care either.

Using the described data and methods, I find no evidence that physician density significantly affects the average self-rated health and diabetes rate in an MSA. My results do not, however, imply that physicians have no positive effect on health. At some point, the health benefits of increasing physician density in a population might plateau off, and my results suggest that this has already happened in the U.S. This suggests that there are enough physicians in U.S. cities and the difference in physician density between cities does not affect the health measures I employ in this paper. The results show that there is evidence of unobserved heterogeneity and endogeneity. Any steps to increase the physician supply should therefore be taken up cautiously.

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Chart 1. Physician Density in the U.S. and selected MSAs - 1998 to 2002

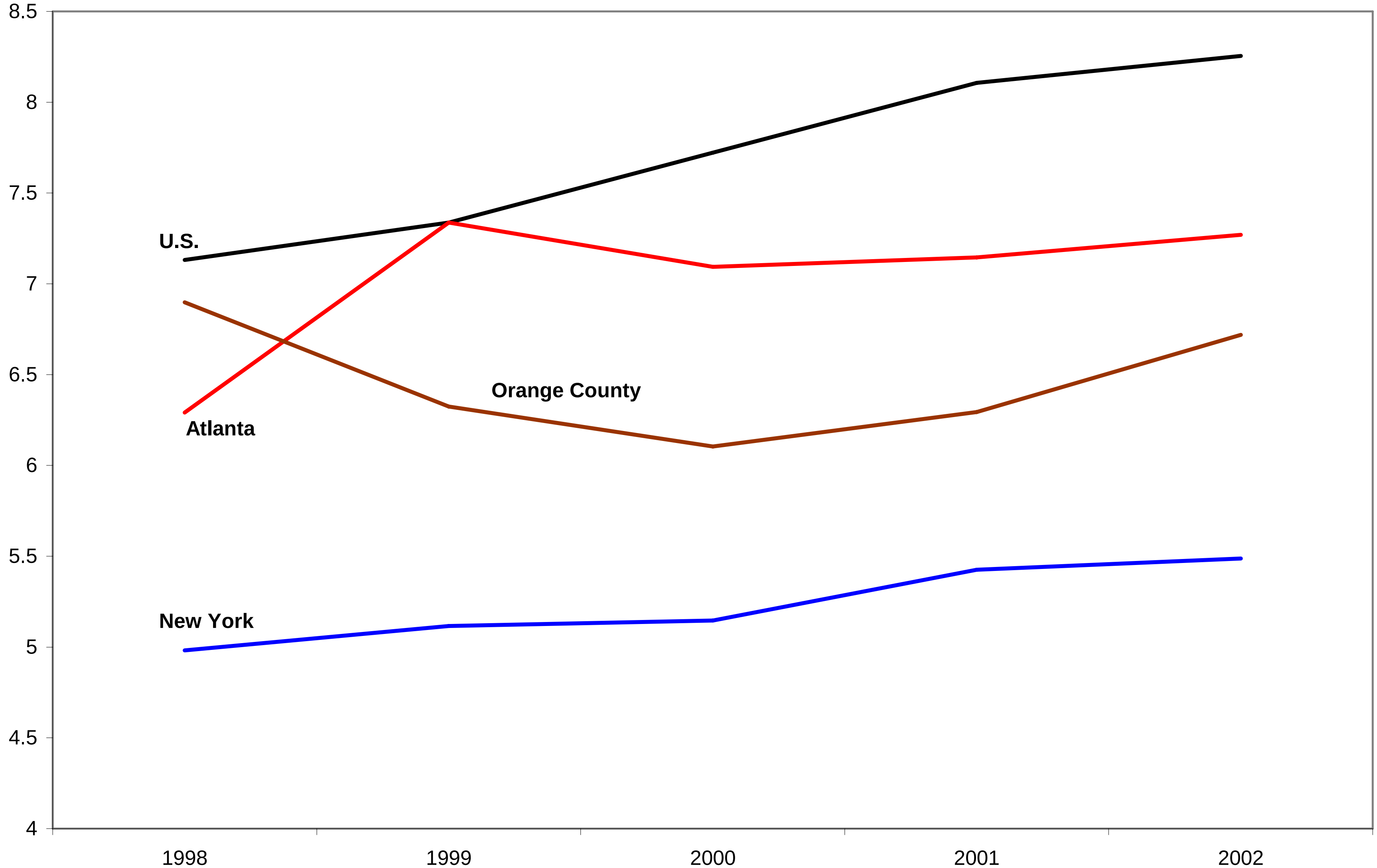

Table 1. Sample Means and Standart Deviations

	Mean	Standard Deviation
Health	2.417	0.108
Diabetes	0.064	0.025
Physician density	7.269	2.384
Age	46.352	2.878
Female	0.596	0.045
Race		
White	0.780	0.143
Black	0.094	0.097
Hispanic	0.081	0.118
Other	0.038	0.030
Education		
Less than Highschool	0.107	0.054
Highschool	0.303	0.074
Some College	0.285	0.053
College	0.305	0.090
Marital Status		
Married or Couple	0.550	0.060
Divorced or Separated	0.169	0.038
Widowed	0.099	0.033
Single	0.180	0.056
Income		
less than $15,000 per year	0.103	0.051
$15,000 - $35,000	0.309	0.063
$35,000 - $50,000	0.163	0.036
more than $50,000	0.291	0.090
unknown	0.134	0.057
Health plan	0.874	0.054
HMO	0.203	0.126
BMI	29.433	1.838
Smoking	0.228	0.047
Research density	0.044	0.172
Birth rate	15.511	3.904
Malpractice payments	13.636	8.059
n	985	

Table 2. Simple OLS Results - MSA level

	Self-rated health	Diabetes
Physician density (1)	0.254***	-0.061**
	(0.086)	(0.029)
Female	-0.109**	-0.023
	(0.048)	(0.016)
Age compared to age 65 and over		
18-29 years	0.106*	-0.015
	(0.057)	(0.019)
30 to 44 years	0.334***	-0.075***
	(0.057)	(0.019)
45 to 64 years	-0.014	-0.049**
	(0.063)	(0.021)
Race compared to White		
Black	-0.158***	0.054***
	(0.023)	(0.008)
Hispanic	-0.163***	0.005
	(0.028)	(0.009)
Other	-0.122	-0.003
	(0.077)	(0.026)
Income compared to <$15,000 per year		
$15-35,000	0.206***	-0.087***
	(0.061)	(0.021)
$35-50,000	0.410***	-0.071***
	(0.071)	(0.024)
> $50,000	0.390***	-0.098***
	(0.057)	(0.020)
unknown	0.346***	-0.121***
	(0.055)	(0.019)
Education compared to less than Highschool		
Highschool degree	0.402***	-0.068***
	(0.069)	(0.023)
Some college	0.588***	-0.070***
	(0.062)	(0.021)
College degree or higher	0.666***	-0.084***
	(0.060)	(0.020)
Health Indicators		
Smoking	-0.220***	0.01
	(0.048)	(0.016)
HMO penetration	0.091***	0.001
	(0.019)	(0.006)
Covered by some healthplan	0.064	0.036*
	(0.056)	(0.019)
BMI	-0.004***	0.002***
	(0.001)	0.000
Observations	985	985
R-Squared	0.71	0.35

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Simple OLS Results - County level

	Self-rated health	Diabetes
Physician density (1)	-0.025***	0.008**
	(0.009)	(0.003)
Female	-0.063***	-0.011***
	(0.013)	(0.004)
Age compared to age 65 and over		
18-29 years	0.085***	-0.025***
	(0.017)	(0.005)
30 to 44 years	0.199***	-0.048***
	(0.015)	(0.005)
45 to 64 years	0.114***	-0.044***
	(0.017)	(0.005)
Race compared to White		
Black	-0.104***	0.066***
	(0.007)	(0.002)
Hispanic	-0.078***	0.006**
	(0.008)	(0.003)
Other	-0.070***	0.039***
	(0.011)	(0.003)
Income compared to <$15,000 per year		
$15-35,000	0.410***	-0.065***
	(0.019)	(0.006)
$35-50,000	0.578***	-0.073***
	(0.021)	(0.007)
> $50,000	0.517***	-0.069***
	(0.017)	(0.006)
unknown	0.364***	-0.079***
	(0.017)	(0.006)
Education compared to less than Highschool		
Highschool degree	0.633***	-0.055***
	(0.017)	(0.006)
Some college	0.751***	-0.070***
	(0.016)	(0.005)
College degree or higher	0.913***	-0.092***
	(0.016)	(0.005)
Health Indicators		
Smoking	-0.298***	0.027***
	(0.013)	(0.004)
Covered by some healthplan	0.071***	0.031***
	(0.015)	(0.005)
BMI	-0.005***	0.001***
	0.000	0.000
Observations	4843	4843
R-Squared	0.71	0.35

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Fixed Effects Results - MSA level

	Self-rated health	Diabetes
Physician density (1)	-0.007	-0.016
	(0.357)	(0.132)
Female	-0.031	-0.023
	-0.05	-0.019
Age compared to age 65 and over		
18-29 years	0.138*	-0.053**
	-0.072	-0.026
30 to 44 years	0.224***	-0.072***
	(0.064)	(0.024)
45 to 64 years	0.165**	-0.088***
	(0.077)	(0.029)
Race compared to White		
Black	-0.164**	0.036
	(0.079)	(0.029)
Hispanic	-0.201**	0.004
	(0.101)	(0.037)
Other	0.014	0.001
	(0.121)	(0.044)
Income compared to <$15,000 per year		
$15-35,000	0.275***	-0.098***
	(0.079)	(0.029)
$35-50,000	0.404***	-0.073**
	(0.092)	(0.034)
> $50,000	0.340***	-0.124***
	(0.087)	(0.032)
unknown	0.427***	-0.126***
	(0.081)	(0.030)
Education compared to less than Highschool		
Highschool degree	0.189**	-0.063*
	(0.089)	(0.033)
Some college	0.311***	-0.013
	(0.091)	(0.034)
College degree or higher	0.465***	-0.003
	(0.094)	(0.035)
Health Indicators		
Smoking	-0.075	0.011
	(0.062)	(0.023)
HMO penetration	0.103	0.046
	(0.105)	(0.039)
Covered by some healthplan	0.084	0.026
	(0.079)	(0.029)
BMI	-0.003**	0.001**
	(0.001)	(0.001)
Observations	985	985
R-Squared	0.29	0.23

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported
Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. First Stage in Instrumental Variable Estimation - MSA level

	Physician Density (1)
Research institutions per 1000 people	0.196
	(0.230)
Birth rate	0.009***
	(0.003)
Malpractice payments per employee	-0.0001***
	(0.000)
Female	-0.027*
	(0.015)
Age compared to age 65 and over	
18-29 years	-0.031*
	(0.018)
30 to 44 years	0.002
	(0.018)
45 to 64 years	-0.024
	(0.020)
Race compared to White	
Black	-0.012
	(0.008)
Hispanic	-0.051***
	(0.009)
Other	-0.036
	(0.024)
Income compared to <$15,000 per year	
$15-35,000	-0.036*
	(0.020)
$35-50,000	-0.081***
	(0.023)
> $50,000	-0.066***
	(0.019)
unknown	-0.043**
	(0.018)
Education compared to less than Highschool	
Highschool degree	-0.002
	(0.023)
Some college	-0.008
	(0.021)
College degree or higher	0.035*
	(0.021)
Health Indicators	
Smoking	0.017
	(0.015)
HMO penetration	-0.017***
	(0.006)
Covered by some healthplan	-0.038
	(0.239)
BMI	0.004
	(0.006)
Observations	903
R-squared	0.190

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported
Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Instrumental Variable Results - MSA level

	Self-rated health	Diabetes
Physician density (1)	1.176	-0.255
	(0.905)	(0.235)
Female	-0.115**	-0.017
	(0.055)	(0.018)
Age compared to age 65 and over		
18-29 years	0.093	(0.013)
	(0.062)	(0.021)
30 to 44 years	0.336***	-0.083***
	(0.061)	(0.020)
45 to 64 years	-0.037	-0.046**
	(0.067)	(0.022)
Race compared to White		
Black	-0.144***	0.054***
	(0.027)	(0.009)
Hispanic	-0.127***	-0.006
	(0.044)	(0.015)
Other	-0.098	-0.005
	(0.084)	(0.028)
Income compared to <$15,000 per year		
$15-35,000	0.234***	-0.100***
	(0.072)	(0.024)
$35-50,000	0.446***	-0.097***
	(0.099)	(0.033)
> $50,000	0.450***	-0.124***
	(0.080)	(0.027)
unknown	0.372***	-0.148***
	(0.069)	(0.023)
Education compared to less than Highschool		
Highschool degree	0.405***	-0.059**
	(0.077)	(0.025)
Some college	0.599***	-0.068***
	(0.069)	(0.023)
College degree or higher	0.612***	-0.067***
	(0.071)	(0.024)
Health Indicators		
Smoking	-0.245***	0.013
	(0.051)	(0.017)
HMO penetration	0.115***	-0.007
	(0.026)	(0.009)
Covered by some healthplan	0.056	0.040**
	(0.060)	(0.020)
BMI	-0.004***	0.002***
	(0.001)	0.000
Observations	903	903

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported
Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Instrumental Variable with First Differencing Results - MSA level

	Self-rated health	Diabetes
Physician density (1)	5.414	1.205
	(8.304)	(2.803)
Female	-0.015	0.017
	(0.061)	(0.021)
Age compared to age 65 and over		
18-29 years	0.088	-0.054*
	(0.083)	(0.028)
30 to 44 years	0.294***	-0.118***
	(0.083)	(0.028)
45 to 64 years	0.078	-0.065**
	(0.095)	(0.032)
Race compared to White		
Black	-0.136	0.108***
	(0.098)	(0.033)
Hispanic	-0.230*	0.009
	(0.129)	(0.044)
Other	0.068	0.022
	(0.137)	(0.046)
Income compared to <$15,000 per year		
$15-35,000	0.208**	-0.134***
	(0.101)	(0.034)
$35-50,000	0.367***	-0.107***
	(0.108)	(0.036)
> $50,000	0.337***	-0.183***
	(0.120)	(0.041)
unknown	0.436***	-0.173***
	(0.104)	(0.035)
Education compared to less than Highschool		
Highschool degree	0.232*	-0.096**
	(0.124)	(0.042)
Some college	0.385***	-0.069
	(0.133)	(0.045)
College degree or higher	0.468***	-0.029
	(0.122)	(0.041)
Health Indicators		
Smoking	0.032	0.005
	(0.086)	(0.029)
HMO penetration	0.044	-0.058
	(0.237)	(0.080)
Covered by some healthplan	0.058	0.045
	(0.118)	(0.040)
BMI	-0.005***	0.001
	(0.002)	(0.001)
Observations	649	649

(1) = workers in physicians offices per 10 people
Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. First Stage in First Difference Instrumental Variable Estimation MSA level

	Physician Density (1)
Research institutions per 1000 people	0.001
	(0.029)
Birth rate	0.001
	(0.002)
Malpractice payments per employee	-0.001*
	(0.001)
Female	0.001
	(0.001)
Age compared to age 65 and over	
18-29 years	-0.004
	(0.007)
30 to 44 years	0.005
	(0.008)
45 to 64 years	-0.0001
	(0.010)
Race compared to White	
Black	-0.003
	(0.007)
Hispanic	0.006
	(0.008)
Other	0.002
	(0.010)
Income compared to <$15,000 per year	
$15-35,000	0.005
	(0.007)
$35-50,000	0.002
	(0.008)
> $50,000	0.008
	(0.007)
unknown	-0.001
	(0.007)
Education compared to less than Highschool	
Highschool degree	-0.007
	(0.007)
Some college	-0.006
	(0.008)
College degree or higher	-0.006
	(0.006)
Health Indicators	
Smoking	-0.006
	(0.005)
HMO penetration	0.014
	(0.015)
Covered by some healthplan	-0.011*
	(0.006)
BMI	0.001
	(0.001)
Observations	649
R-squared	0.023

(1) = workers in physicians offices per 10 people; Year effects also estimated although not reported
Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Effect of physician density on health variables with interactions - MSA level

	Ordinary Least Squares		**Fixed effects**		**Instrumental variable**	
	Self-rated health	Diabetes	Self-rated health	Diabetes	Self-rated health	Diabetes
Physician Density	5.592**	-0.650	9.039	0.975	3.702	0.226
	(2.184)	(0.745)	(15.274)	(1.207)	(15.353)	(5.224)
Physician Density*Income $15-35,000	7.325***	-1.120	0.724	-1.667	1.631	-0.521
	(2.485)	(0.848)	(3.080)	(1.136)	(9.327)	(3.174)
Physician Density*Income $35-50,000	8.281***	-0.652	1.114	-1.652	3.859	-1.271
	(2.793)	(0.953)	(3.750)	(1.383)	(6.527)	(2.221)
Physician Density*Income > $50,000	5.234**	0.116	-0.992	-0.652	0.841	0.667
	(2.089)	(0.713)	(3.255)	(1.200)	(6.894)	(2.346)
Physician Density*Income Unknown	3.697	0.131	-0.299	-0.674	-2.666	-0.054
	(2.429)	(0.829)	(3.496)	(1.289)	(8.560)	(2.913)
Physician Density*High school degree	-0.525	-0.449	7.674**	0.634	-6.816	0.298
	(2.496)	(0.852)	(3.314)	(1.222)	(10.265)	(3.493)
Physician Density*Some college	-0.161	0.224	10.502***	1.068	-4.595	0.255
	(1.938)	(0.661)	(3.725)	(1.374)	(10.375)	(3.530)
Physician Density*College	1.437	-0.764	11.829***	-1.308	-3.73	-0.804
	(1.988)	(0.678)	(3.954)	(1.458)	(8.878)	(3.021)

Other variables included in the estimations though not reported include: percent of MSA in age categories 18-29, 30 to 44, and 45 to 65, percent of MSA female, percent of MSA Black, Hispanic, and other, percent of MSA in yearly income categories $15,000-$35,000, $35,000-$50,000, >$50,000, and unknown, percent of MSA in educational categories High School, Some college, and College, percent of MSA that smokes, is covered by some health plan, HMO penetration, average BMI in an MSA, and year effects.

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%