Fatal Attraction:

health care agglomeration and its consequences

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Abstract

In this paper we focus on what seems to be a fundamental tension between the economies of agglomeration available to health care organizations and the impacts of spatial concentration of health care organizations on overall health outcomes.

We identify plausible measures of health care concentration and dispersion, and adapt them to the US urban context. We calculate these measures for nonprofit health organizations for all US metropolitan areas from 1989 to 2009. We use these data to test for signs that agglomeration economies are important for these organizations.

We use mortality rates to serve as an indicator of health outcomes, and provide an analysis of the impacts of agglomeration on health outcomes in US cities. This analysis highlights some disturbing results. The analysis suggests that health care organizations in US cities are more clustered than desirable for achieving the best health outcomes.

1 Introduction

When a person is seriously unwell or injured, it is natural that they want to receive health care without delay. Minimizing the delay associated with providing health care will be facilitated by health care organizations that are dispersed throughout cities to reduce the expected travel time to clinical care. Even when urgent or clinical care is not required, having health care organizations that are dispersed rather than clustered may increase the exposure of residents to health care production, helping to remind them of the importance of healthy living and improving the ease with which health care information can be obtained. Thus for a combination of reasons, dispersion of health care organizations might be associated with improved health outcomes.

Production of health care services is a complex and technical process. Providing the highest-quality health care requires the coordinated efforts of highly skilled labor whose training and experience enable practitioners to combine rapidly-changing technology with the need for individualized personal communication for the best outcome. The changing nature of the technology and the centrality of finding the most skilled labor, as well as maintaining the skills of existing health care workers, suggests that health care service production is likely to exhibit significant economies of agglomeration. Having multiple providers of clinical health care and related services located near one another can provide all of the advantages usually associated with localization economies. A common labor pool provides a rewarding environment for skilled workers to offer their services. It provides them with opportunities to learn from one another. Having the clinic where physicians meet patients near the hospitals where patients receive care that requires specialized services, and having both near laboratory or research facilities can help physicians and other health care providers work more efficiently and make use of the latest discoveries and technological improvements. This requires the clustering together of health care organizations, so it is also plausible that concentration, and not dispersion, may be associated with improved health outcomes.

What is the net effect of these two forces? Does concentration of health care production improve or diminish health outcomes? Is there any reason to expect that health care organizations will arrange themselves in such a way as to maximize the health benefits to the population they serve? Alternatively, if agglomeration economies are present, do they pursue these economies seeking the benefits for the individual organizations but neglecting to account for the external impact on community health that might be associated with their location?

There are few papers that have examined the impact of agglomeration in the health care sector on health outcomes. Moreover, the ones that have performed this analysis used rough measures of agglomeration that might be criticized as providing an imperfect measure of service concentration or dispersion.

Sundmacher & Busse (2011) studied the impact of physician supply on avoidable cancer deaths in Germany. Avoidable Cancer Deaths, known as ACD, are cancer deaths that are adjusted for higher mortality rates at older ages. According to Sundmacher and Busse, given the appropriate timing and access to care, certain types of deaths should not occur in individuals of specific age groups. Sundmacher and Busse identified these avoidable cancer deaths using the ICD-10 codes for the five years from 2000 to 2004. Furthermore, they calculated the ACD rates for the 439 German counties resulting in a panel of 2195 observations. To measure hospital services, they used physicians, beds and specialized beds per 100,000 population. When controlling for other important factors such as smoking rate, fertility, unemployment rate, education and income, Sundmacher and Busse found that physician supply had a small impact on ACD rates. According to a result given in the paper, in a district with population of 100,000 and 15 ACDs, an increase in physician supply of 10 would lead to one less ACD over the 5 year period. When controlling for other variables, they found that neither hospital bed supply nor specialized bed supply had a significant impact on ACD rates. Although this serves as evidence for the impact of health care agglomeration on health outcomes, it is important to note that the variables used to measure density do not provide any information on the distribution of health care providers.

Recent studies by Li (2013) and Li (2014) also consider the impact of health care provider agglomeration on health outcomes. She examines the mortality per population from 1999 to 2007 at the county level. Her dependent variables are the heart disease, stroke and cancer rates per population. To study the impact of agglomeration, she measures her explanatory variables at two concentric rings where an increase in health care providers in the first ring corresponds to an increase in agglomeration. The radius of the first ring is from 0 to 25 miles from the geographic center while the radius of the second is from 25 to 50 miles. Li also accounts for cross state boundaries and includes the number of in-state and out-of-state levels for each variable hypothesizing a smaller effect of out-of-state variables. Li controls for the number of specialists per bed, the number of nurses per bed and the number of hospital beds as well as state fixed effects. Her first regression includes all of these variables at the 0-25 mile range measuring both in-state and out-of-state levels while her second regression includes both the 0-25 mile range and the 25-50 mile range for all variables at the in-state and out-of-state levels. Her results show that an increase in the in-state number of specialists per bed at the 0-25 mile range has a significant negative impact on death rates for all mortality rates. She also finds that the impact of doctors further away tends to be small and insignificant. Li comes closer to accounting for distributional differences as the area of the 0 to 25 mile ring is much smaller than that of the 25-50 mile ring. As a result if both rings experience an increase in 10 doctors per bed, the corresponding increase in density will be higher in the 0 to 25 mile ring due to the smaller area.

Although they do not directly assess the impact of health care agglomeration on health outcomes, Bates & Santerre (2005) evaluate the impact of health care provider agglomeration on productivity. To measure hospital output they use adjusted inpatient days which are a weighted sum of inpatient and outpatient days. They study the U.S. MSAs in the years 1993 and 1999. They estimate a production function where adjusted inpatient days are a function of labor and beds. The four different labor inputs are total nurses, physicians and dentists, other salaried personnel and admitting physicians. Also included in the model are HMO penetration rates with the predicted relationship being that HMOs cause hospitals to be more efficient. Their first difference approach finds that when controlling for the labor inputs, HMO penetration rates, population, and income, the number of hospitals per capita has a highly significant impact on productivity. Thus they find that agglomeration economies do exist in the health care provider sector and have a large impact on productivity.

It has been suggested that an increase in hospital clustering could result in people having to travel further to the emergency room leading to a rise in death rates offsetting the gains from agglomeration. Interestingly, Buchmueller, Jacobson & Wold (2006) find support for this relationship in their experiment. They study the impact of hospital closures in Los Angeles between 1997 and 2003 on health outcomes. Using data on hospital utilization and location, they calculate changes in distance to the nearest hospital from the center of each zip code in Los Angeles County. Their health outcome variables come from both birth and mortality data. They use time sensitive mortality data such as heart attack deaths and deaths due to unintentional injury. Also incorporated in the model are health outcomes that are hypothesized to be less time sensitive such as deaths from colon and lung cancer and chronic ischemic heart disease. In their analysis, Buchmueller, Jacobson and Wold estimate that an increase in hospital distance of 1 mile leads to nearly a 3% increase in deaths due to heart attacks (AMIs).

A final possible source of economic benefits from concentration might come from the increasing levels of service provision that may be associated with either consolidation or specialization in provision of certain types of health care. If a clinic or hospital specializes in provision of orthopedic care, for example, it might be able to improve the quality of hip, joint and back care provided because the specialization has facilitated higher rates of production or "throughput" of patients. This specialization may in turn be facilitated by proximate location with other clinics and health care providers that do not specialize in such care. There is some evidence that increased throughput is associated with improved health outcomes.

Halm, Lee & Chassin (2002) provide a survey of such evidence. They consider over 270 articles that investigated the impact of physician and hospital volume on death rates. They also categorized the articles based on the level of risk adjustment used for preexisting patient factors such as disease severity. Studies were classified into 4 risk adjustment categories.

The analyzes surveyed typically looked at individual patients suffering from one or more conditions. The studies tracked which hospitals and physicians provided treatment as well as the patient outcomes. Using these data they create a mortality ratio for high/low volume hospitals and calculate the difference. The survey reports the median mortality difference between high/low volume hospitals.

The analysis finds that for a majority of studies (approximately 70%), hospital and physician volume were negatively related to mortality rates. That is, an increase in volume led to a decrease in mortality. The most consistent relationship between volume and mortality was found for high risk procedures. Most studies do not look at the relationship between volume and mortality over time. More importantly, the studies that tracked individual hospitals found that changes in a hospital's volume over time had no or minimal effects on outcomes. This raises a concern about selection effects in the data. Patients may choose to go to hospitals due to reports of better outcomes. As more people choose to go to an individual hospital this raises volume. Thus volume is determined by how "good" a hospital is, rather than volume being a factor that influences the quality of service.

In summary, the literature on the links between clustering or dispersion of health care providers and health outcomes is modest in volume and somewhat inconclusive about the relationship. In what follows we hope to make a contribution to the understanding of this issue. In section 2 we describe the approach we take to identifying measures of clustering of health care organizations. In section 3 we describe a simple theoretical approach that permits a type of test for agglomeration economies using the data we have available. In section 4 we describe the actual data assembled for our panel, and in sections 5 and 6 we present the central results of our estimation.

2 Measuring concentration and dispersion

When we examine the patterns of locations occupied by health care organizations, it can be difficult to know whether the pattern has arisen due to natural or economic forces that enhance the sustainability of health care producers that are concentrated at particular points, or the product of accident arising from random location choices. Whether it is better to call the clusters that do occur *natural* or *accidental* depends on what is expected to occur. Such expectations are generally based on experience in actual cities and from looking at the location patterns of other similar organizations.

Beyond the question of whether the observed pattern of locations is random, the product of conscious choice or some systemic pressure that tends to eliminate organizations that end up in one type of location rather than another, we must contend with the practical matter of devising some measures of concentration and dispersion. Simply calculating the number of organizations per capita or per square kilometer is unlikely to capture what we want. Population figures for per capita measurements are available only for particular jurisdictions (counties, municipalities, census tracts, etc.) and the measured density per capita is very sensitive to the particular jurisdiction. Since these jurisdictions have geographic boundaries created at different times for a variety of idiosyncratic reasons, measures of organizations per capita will reflect some of those reasons. Measures of density per unit area are also problematic. Measures of organizations per unit land area don't necessarily reflect the direct source of agglomeration economies – the proximity to other health care producers – and in any event they won't necessarily reflect the concentration or dispersion of organizations relative to the set of possible locations. These possible locations reflect both the variation in density of demand for health care services as well as the set of locations where it is even possible for such an organization to become established.

While no set of indicators is perfect, we develop and use measurements of how the concentration of health care nonprofits compares to the concentration of other nonprofit organizations. This is inspired by the analysis of industrial location first presented by Duranton & Overman (2005) and applied by them to analyze the location of manufacturing in Britain in Duranton & Overman (2008). The approach has since been applied to describe and analyze location, co-location and the effects of policies in a variety of settings[1].

We regard the set of all nonprofit organizations in a city as representing a set of locations where health care organizations *might* locate. We take the set of all health care organizations and determine the set of distances between each pair. For a city with N organizations there will be $\frac{N^2-N}{2}$ such pairs, each with a particular distance. We obtain a kernel estimate of the density of distances between health care organizations. The median value θ of this density provides an overall measure of concentration of health care organizations in the urban area.

To calculate whether health care organizations are locally concentrated relative to the set of possible locations, we proceed to draw 1000 samples of N nonprofit organizations in the city that are not involved in producing health care. For each draw, we repeat the procedure, calculating the distances between all pairs of organizations and obtaining a kernel estimate of the density of distances.

After completing these calculations we calculate the 5^{th} and 95^{th} percentile of the densities of distances for non-health organizations. An index of clustering λ is set to 1 if the density of health organizations rises above the 95^{th} percentile of the densities of non-health organizations in the first half of the range of distances. If the density of health organizations is not clustered, but does fall below the 5^{th} percentile of the densities of distances for non-health organizations, then we regard the health organizations as dispersed and set an index of dispersion δ equal to 1. If the density of distances stays within the 5^{th} and 95^{th} percentiles of the densities of distances for non-health organizations for the first half of the distances then we have $\lambda = \delta = 0$.

[1] See for example Billings & Johnson (2014).

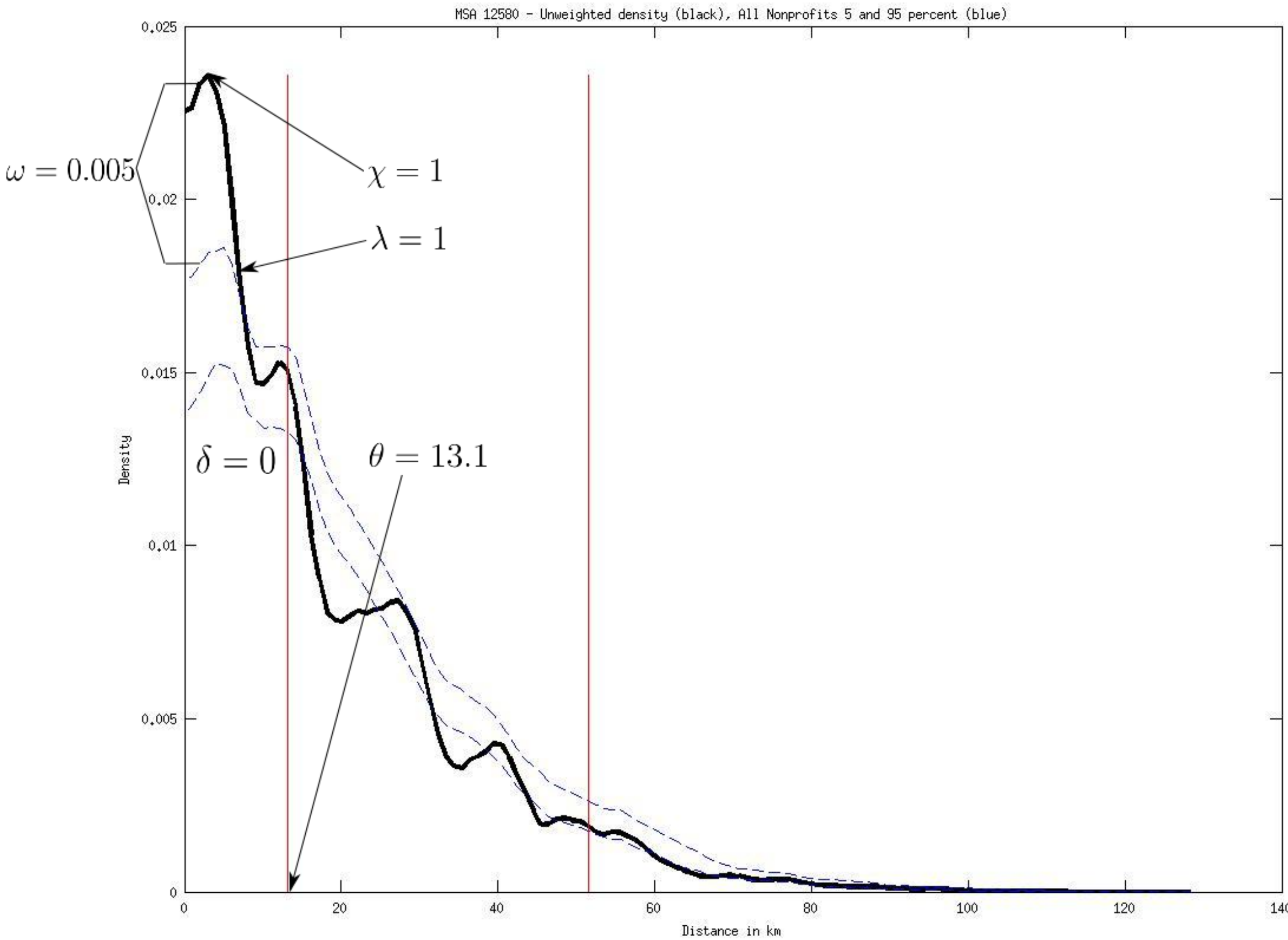

Figure 1: Density of distances for Baltimore, MD

There are two additional measures we calculate. When the density of health organization distances rises above the 95^{th} percentile of densities for non-health organizations, we often observe local "peaks". These may indicate distinct clusters of health care organizations in the urban area. We provide a count χ of the number of these significant peaks. Finally, we measure the maximum gap ω between the density of distances of health organizations and the 95^{th} percentile of densities for non-health organizations. When this value is large it may indicate greater opportunities for clusters to develop at some scale.

An example of these calculations is presented in Figure 1. The dark heavy line is the estimated density of distances between health care organizations in Baltimore, Maryland for 2009. The median distance between the health care organizations is 13.1 kilometers. The density rises to a single peak above the 95^{th} percentile of densities for non-health organizations, so we have $\chi = \lambda = 1$ and $\delta = 0$. The maximum gap between the densities is given by $\omega = 0.005$

In summary, we have applied a variation of the microgeographic analysis of location introduced by Duranton & Overman (2005) and from that analysis derived several measures that can be used for analysis of the concentration or dispersion of health care organizations. We focus on the potential value of five different measures of clustering or agglomeration of health care nonprofits:

1. A dichotomous cluster indicator variable λ that indicates whether at some scale health care nonprofits are more clustered $(\lambda = 1)$ than all other nonprofits;

2. The median distance θ between health care nonprofits;

3. The number of significant peaks χ – distinct distances at which the density of health care nonprofits exceeds the 95^{th} percentile of the density on all nonprofits;

4. The maximum difference ω between the density of health care nonprofits and the 95^{th} percentile of the density of all nonprofits;

5. An indicator δ that takes the value 1 if $\lambda = 0$ and the density of distances between health care organizations falls below the 5^{th} percentile of the density of distances between all nonprofits;

All of these measures, based on microgeographic data about the location of organizations, avoid the distortions of measuring the numbers of organizations per census tract, zip code, county, metro area, or state. As mentioned above, these more traditional measures of concentration make comparison between cities or regions more difficult or impossible.

3 A simple model of health care concentration

Consider an organization operating to produce health care services in a setting where other organizations producing similar services may choose to operate. These might be organizations of any type, ranging from small clinics, imaging or analysis laboratories to major hospitals offering a wide variety of emergency, inpatient and outpatient services.

Actual markets contain public agencies,[2] private for-profit investor-owned entities[3] and nonprofit organizations.[4] Our analysis here excludes the public agencies, and our data analysis focuses on the nonprofit sector, which contains a sizable majority of the hospitals and clinical care facilities in the US.

Nonprofit health care providers do not have a group of investors who receive surplus revenues from operation, but they certainly do compete with each other (including investor-owned providers) and face market constraints on the prices that can be charged. They are subject to the constraint of *economic sustainability*, which requires that they cover the costs of providing the services that have been chosen as a focus by the governing board of the organization. They face a limited demand for their services and choose to operate if they can cover all costs. If they cannot, they do not open (or do not survive). They differentiate themselves from other health care providers by convenience, service specialty, and quality.

We adapt the closed economy model of Melitz & Ottaviano (2008) to provide a framework for thinking about how agglomeration economies might influence the number and type of health care organizations we observe in an urban area. We provide the outline of such an interpretation here, retaining the notation of Melitz & Ottaviano (2008) for ease in comparison. This model presents a set of monopolistic-competitive producers that we argue provide a reasonable approximation of health care providers. The products are (or may be) differentiated and perceived by consumers as unique to each health care provider. Demand for health care can reflect the overall level of demand for the services and the substitutability between the services. Health care organizations continue to enter the market until the marginal organization can just barely cover costs, and no other organizations could enter and earn sufficient revenues to cover the costs of production.

Health care organizations experience a variety of influences on their costs of service provision. Among these are the levels of agglomeration or dispersion in available locations in an urban area. If the city already has some developed clusters of health care providers, the probability is higher that a health care organization will secure a location near others and experience lower costs. We assume that owners of potential locations are too competitive and that health care organization locations are too small of a share of the commercial location market to warrant owners of space organizing these clusters. Some

[2]Such as the US Veterans Administration and its many VA Hospitals around the country.

[3]Such as Methodist Hospital in San Antonio, TX, the largest for-profit hospital in the US

[4]Such as New York Presbyterian Hospital/Weill Cornell Medical Center in New York City, the largest nonprofit hospital in the US.

concentrations will arise randomly as a city grows, and markets with such natural clusters will offer potential entrants with a different distribution of possible costs of production.

Consider a region of L identical consumers, each having preferences that are separable between health care services and other goods. Health care services are produced by health care organizations and indexed by $i \in \Omega$. Total consumption of all health care is given by

$$Q^C = \int_{i \in \Omega} q_i^C di \tag{1}$$

Households derive utility from these goods and services and supply one unit of labor to earn income used to purchase health care. Separable utility permits focus on the allocation of this income amongst the types of health care goods and services. Expenditures on other goods is not, and need not be, of concern in the discussion below.

Consumers have identical utility functions, and the portion of their utility function that determines the utility of health care services is as described in Melitz & Ottaviano (2008), so that the inverse demand for each type of health care is given by:

$$p_i = \alpha - \gamma \cdot q_i^C - \eta \cdot Q^C \tag{2}$$

for $q_i^C > 0$. Thus $\gamma = 0$ implies that all health care goods and services are perfect substitutes and consumers care only about the total of all such goods consumed. As γ increases health care services become increasingly differentiated from one another.

The subset of health care services consumed is $\Omega^* \subseteq \Omega$, identified by the set of indices for which the price of the good p_i is less than the price that would make demand $q_i^C = 0$. The measure of the types of health care actually consumed, Ω^*, is N. We identify this with the number of active health care organizations. The average price of health care consumed is:

$$\bar{p} = \frac{1}{N} \cdot \int_{i \in \Omega^*} p_i di \tag{3}$$

As noted in Melitz & Ottaviano (2008) this demand system exhibits a preference for variety so that the

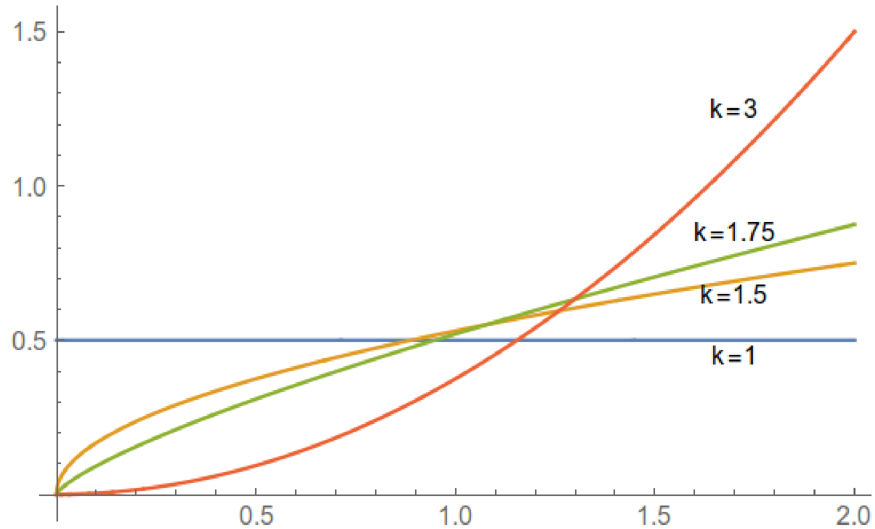

Figure 2: Distribution of marginal cost at alternative values of k

utility of consumers rises as N increases, which seems sensible for health care goods and services.

The cost of producing health care c is a random variable whose reciprocal $\frac{1}{c}$ (which can be thought of as the *efficiency* of the health care provider) is distributed according to a Pareto distribution with scale parameter $\frac{1}{c_m}$ and shape parameter k, with $k \geqslant 1$ required for efficiency to have a finite mean. The value of the parameter c_m is the maximum marginal cost of production for health care. When $k = 1$ the marginal cost values c are uniformly distributed between 0 and c_m. As k rises, the distribution becomes less favourable for health care production, bunching organizations increasingly towards the higher cost portion of the interval $(0, c_m)$. Figure 2 illustrates the distribution for four alternative values of k, all with maximum marginal cost $c_m = 2$.

Each health care organization that enters this market produces a single variety of health care service, and must pay a fixed cost f_E to enter the market. After paying this fixed cost, the organization learns the constant marginal cost of service provision $c \in (0, c_m)$ where c_m is the upper bound of possible marginal production costs. The level of fixed costs f_E associated with opening in the market, along with the level of demand, will determine a maximum sustainable cost level c_D, where the organization revenues are just capable of covering production costs. We follow Melitz & Ottaviano (2008) in assuming that the level of f_E and other parameters are such that $c_D < c_m$ and the equilibrium with free entry of organizations produces a well-defined solution. Organizations whose costs c are below c_D will operate and produce health care services $i \in \Omega^*$, and as noted above there will be N of these.

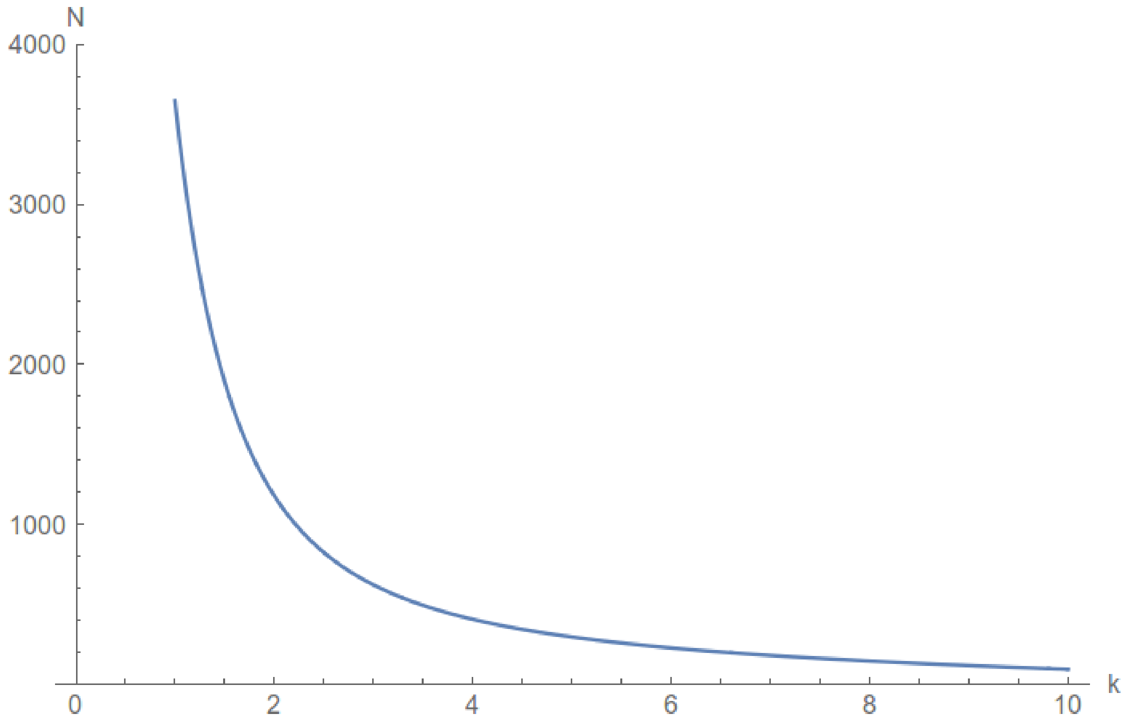

Figure 3: Active health care organizations as a function of k

The shape parameter k for the Pareto distribution of efficiency levels is critical in determining the number of active organizations in the region, the aggregate level of surplus revenues, and the level of health care provision in the region. Melitz & Ottaviano (2008) show that there is a cutoff level of costs c_D that determines which organizations will be active producers in equilibrium. If the random variable $c > c_D$ then the organization will not be active. For the cost distribution identified above this cutoff level of costs will be:

$$c_D = \left[2 \frac{(k+1) \cdot (k+2) \cdot \gamma \cdot c_m^k \cdot f_E}{L} \right]^{\frac{1}{k+2}} \tag{4}$$

The number of organizations active in equilibrium in the region is then given by:

$$N = \frac{2 \cdot (k+1) \cdot \gamma}{\eta} \cdot \frac{\alpha - c_D}{c_D}. \tag{5}$$

Using reasonable values for parameters[5] that satisfy the restrictions assumed here and in Melitz & Ottaviano (2008), the relationship between the efficiency distribution shape parameter k and the number

[5]The examples take $f_E = 10000, c_M = 10000, L = 100000, \gamma = 10, \alpha = 5000, \eta = 1.1$ but qualitatively are not sensitive to these values as long as other restrictions apply.

of organizations active in equilibrium is illustrated in Figure 3.

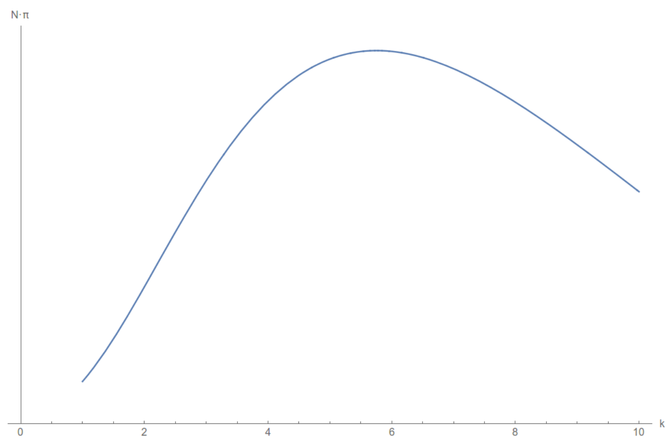

Figure 4: Total surplus revenue

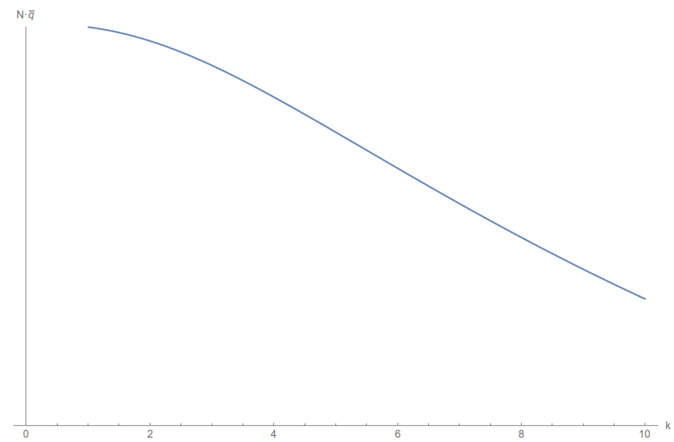

Figure 5: Total health care production

Melitz & Ottaviano (2008) derive the average surplus revenues and average organization output. Using these derivations, along with the number of organizations presented in equation 5 and illustrated in Figure 3 we can examine the relation between k and the total surplus revenue earned by all health care providers combined, as well as the total production of health care services. These are illustrated in Figures 4 and 5, respectively.

When an organization opens in the region, it will be confronted with a range of location options. The location available to the new health care organization will be part of the source of random variation in the costs of production. If health care providers in the region are clustered together so that they can share inputs, find labor matches in common pools, and in other ways learn from each other or benefit from proximity to one another then their costs will tend to be lower. If the region is one where locations available to organizations are more dispersed and isolated, then their costs will tend to be higher. We use the parameter k to capture these impacts of available agglomeration or location within these concentrations.

If the extent of agglomeration in the area determines the distribution of costs that organizations may experience, it is natural to assume that the shape parameter k depends on the extent of agglomeration. In section 2 we identified measures that provided an index of relative concentration λ, the number of peaks in the density of distances χ, the median distance between organizations θ, the maximum gap ω between the density of distances between health care producers and the 95^{th} percentile of densities of distances between other nonprofits, and an index δ that provides an indication of when health care organizations are dispersed relative to other nonprofits.

We assume that $k = k(\lambda, \chi, \theta, \omega, \delta)$, and if agglomeration economies are important for health care producers we would further expect that:

$$k_\lambda < 0 \quad \Rightarrow \quad \text{concentration implies lower costs} \tag{6}$$

$$k_\chi < 0 \quad \Rightarrow \quad \text{more "peaks" implies lower costs} \tag{7}$$

These expectations follow from the relatively unambiguous nature of the measures λ and χ. An increase of λ from zero to one is a clear indication that at a relevant scale health care producers are more concentrated than other nonprofit organizations. An increase in χ may be a signal that there are a larger number of local concentrations of health care producers, and this increases the chance that a potential producer will find a location near one of them. If an increase in the median distance between health care producers θ occurs, holding the urban area and number of organizations N constant, then a random health care producer would expect to travel farther in order to have contact with half of the other health care organizations in the city. Therefore we also expect:

$$k_\theta > 0 \quad \Rightarrow \quad \text{greater distance between organizations implies higher costs} \tag{8}$$

Finally, the impact of the maximum difference between the density of health care producers and the density of other nonprofits organizations might indicate more options for agglomeration economies. If the indicator for dispersion δ takes the value one, we expect that a health care organization will have fewer opportunities for locations that provide agglomeration economies so that costs will be higher. These observations may be summarized as:

$$k_\delta \geq 0 \quad \Rightarrow \quad \text{dispersion implies higher costs} \tag{9}$$

$$k_\omega \leq 0 \quad \Rightarrow \quad \text{greater gap implies lower costs} \tag{10}$$

These expected impacts are not simply a matter of "intuition" applied to the health care sector. They are the implication of the adapted model of market size and productivity, coupled with the hypothesis that agglomeration economies will shift the distribution of marginal production costs to lower expected costs for producers who can locate in concentrations.

In the next section we report on the results of calculating each of the concentration measures for all urban areas in the United States for the years 1989 through 2009. We then proceed to estimate models that will put some of these expectations to the test.

4 Data and initial measurement

The data used for analysis are obtained from the Core Financial Files for 501(c)(3) Public Charities available from the National Center for Charitable Statistics (NCCS). These files provide information on all nonprofits in the US that are required to file Form 990 each year with the IRS. This excludes churches (although a few file voluntarily) and it excludes organizations with annual budgets below $25,000. All others are required to file.

The IRS considers each application for tax-exempt status. If it is granted, the IRS makes an initial classification of the charitable purpose of the organization. The NCCS has gone over these classifications and provided alternative corrections based on the current mission statement of the organization or other information available. We have used the NCCS classifications.

For each organization there is at least a zip code, generally a zip+4 code, and in most cases a complete street address. In some cases NCCS has already assigned a latitude and longitude to the organization. We combine this information to determine the most accurate coordinates for each organization possible, and use these to determine the county of location and for the measurement of distances between the organizations.

We have used US Metropolitan Area definitions determined in 2009 by the Office of Management and Budget, and use the same definition for MSAs for all years. We assemble data for 1989 through 2009 for 375 US MSAs, excluding any nonprofits that are not located within the boundaries of an MSA.

The organizations included in our analysis are all in health care related activities but otherwise are a varied group. Figure 6 shows the distribution between broad activity categories. More than 75% of the organizations are involved in providing or supporting the provision of clinical health and mental health care. About 17% of the organizations are professional associations and health advocacy organizations, and about 6% are research organizations. We include these latter groups because they may play important roles in educating the community and in communicating important information to workers in health care organizations.

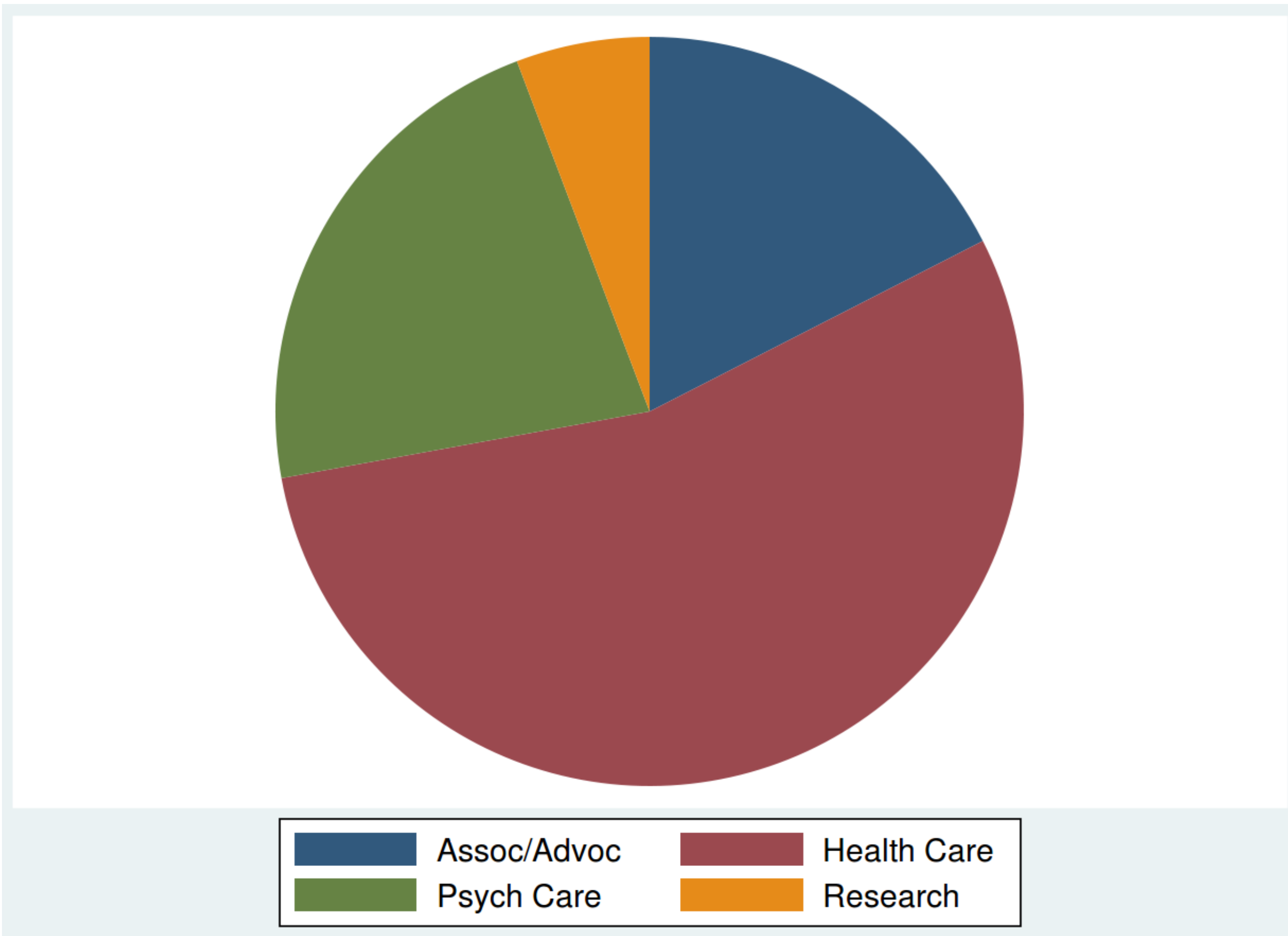

Figure 6: Broad types of health care organizations included in sample

Table 1 provides descriptive statistics for variables used in the analysis, along with mean values for those variables for 1989, 1999 and 2009. These latter values provide a sense of the trend in spatial structure and other variables during the time period covered by our panel. Here we see that median distance between organizations has been rising, and the share of MSAs that are classified as clustered has risen from 46% in 1989 to 62% in 2009. The number of health organizations in each MSA varies widely, from as few as 3 to over 700. The average number of these organizations has risen from fewer

Variable	All years μ	σ	Min	Max	Obs	1989 μ	1999 μ	2009 μ
Mortality all causes	853.0	186.5	309.1	1557.6	7883	845.9	868.8	833.1
θ – Median distance	7.48	6.79	0.001	48.91	7883	7.08	7.37	8.30
λ – Cluster	0.56	0.50	0	1	7883	0.48	0.58	0.62
N – Organizations	62.88	89.35	3	712	7883	46.61	63.20	71.67
Share over 65	0.13	0.03	0.03	0.35	7883	0.12	0.13	0.13
Surplus revenue per org	0.36	0.50	-12.59	8.32	7883	0.36	0.30	0.33
Inpatient days per admit	7.07	3.30	0	51.26	7883	8.82	6.78	5.98
Share black	0.16	0.15	0.00	0.77	7883	0.14	0.16	0.17
Share NB, NW	0.05	0.08	0.00	1.06	7883	0.04	0.05	0.07
χ – Peaks	0.82	1.13	0	11	7883	0.66	0.92	0.80
ω – Gap	0.47	3.29	-0.042	39.454	7883	0.49	0.41	0.55
δ – Dispersed	0.11	0.31	0	1	7883	0.08	0.11	0.08
Cancer death rate	202.1	47.7	66.7	434.4	7883	199.8	205.1	196.8
HD death rate	252.8	75.1	55.8	554.3	7883	287.3	261.2	206.8
Stroke and CA death rate	72.6	21.0	14.4	179.3	7883	78.3	79.7	55.3
Respiratory death rate	81.7	23.6	10.9	202.9	7883	69.7	89.6	86.3
Accident death rate	38.3	10.5	9.2	124.3	7883	39.4	36.5	41.0

Table 1: Descriptive statistics for sample

than 50 to more than 70 during the time period.

In order to measure health outcomes, we obtained Center for Disease Control data on county-level mortality due to various causes. We have aggregated these county-level data up to the same metropolitan areas used in measuring the agglomeration of health organizations. For this analysis we focus on 6 different mortality rates. The overall mortality rate provides the number of deaths per 100,000 persons including deaths from all causes. In addition to this overall mortality rate, we analyze mortality due to cancers of all types, heart attacks and heart disease, strokes and cerebral atheroclerosis, respiratory disease, and accidents of all types. Except for deaths due to accidents, all of these death rates exhibited declines from 1999 to 2009, after exhibiting mixed movement in the first decade of the panel.

5 Agglomeration and the number of health care organizations

Are agglomeration economies present and significant for health care organizations? The model presented in section 3 demonstrates that an increase in the cost distribution parameter k will result in a decrease in the number of active health care organizations, holding other factors constant. We presented in section 3 a set of expected impacts of our measures of agglomeration on the costs of health care organizations. Any factor that raises these costs will reduce the number of organizations per capita in the urban area. In this section we present a direct test of this prediction.

Table 2 presents a set of estimated parameters for 5 models estimated using our panel data. Each has been estimated assuming fixed effects in the panel for each MSA across years. This provides consistent estimates of impacts adjusting for excluded factors that remain constant during the panel period but may vary across metropolitan areas.

All models include the impacts of median distance θ and the index of clustering λ. In the more complete models, θ, λ and χ (the number of peaks) all have the expected sign and are statistically significant, indicating that these measures of agglomeration are associated wtih an increased number of health care organizations per capita, as would be suggested by the model in section 3.

The measures δ and ω do not behave as we expected, which may suggest that these variables are not capturing the extent of agglomeration possibilities as well as θ, λ or χ. We note that the demographic and ethnic structure of the local population are important determinants of the number of organizations. These can be viewed as proxies for the demand variables α, γ and η presented in section 3. Finally, it is interesting to note that increasing surplus revenues (measured as millions of dollars per organization) are associated with decreasing numbers of organizations, as might be suggested by having lower costs (and less intense competition) for the organizations in the area.

Overall, we take the results presented in Table 2 as consistent both with the model presented in section 3 and the maintained hypothesis that agglomeration economies are present and important for health care organizations.

6 Health care agglomeration and health outcomes

The central question posed in Section 1 was whether increasing the concentration and agglomeration of health care producers had a positive or negative impact on health outcomes. We suggested the possibility that the presence of significant agglomeration economies could result in individual health

	Model 1	Model 2	Model 3	Model 4	Model 5
θ – Median distance	-0.062***	-0.063***	-0.027***	0.005	0.006
σ	0.009	0.009	0.010	0.010	0.010
λ – Cluster	0.283***	0.218***	0.311***	0.442***	0.439***
σ	0.053	0.047	0.050	0.052	0.052
Share over 65	43.538***	44.146***	51.831***	56.606***	56.670***
σ	3.107	3.117	3.237	3.386	3.391
Surplus revenue	-0.241***	-0.238***	-0.230***	-0.219***	
σ	0.040	0.040	0.042	0.044	
Inpatient days	-0.142***	-0.143***	-0.299***		
σ	0.012	0.012	0.011		
Share Black	26.746***	27.196***			
σ	1.638	1.644			
Share NW, NB	25.322***	25.390***			
σ	1.623	1.629			
χ – Peaks	0.113***				
σ	0.024				
ω – Gap	-0.020***				
σ	0.006				
δ – Dispersed	0.387***				
σ	0.072				
Constant	1.970***	1.992	7.428	4.388	4.300
σ	0.491	0.492	0.431	0.436	0.436
R^2 – within	0.222	0.216	0.134	0.050	0.047
R^2 – between	0.023	0.027	0.000	0.012	0.012
R^2 – overall	0.013	0.016	0.004	0.015	0.015
σ_u	6.913	6.981	5.257	5.093	5.094
σ_e	1.486	1.493	1.568	1.643	1.645
ρ	0.956	0.956	0.918	0.906	0.906
F	201.710	212.400	197.020	179.570	179.140
F	214.260	294.350	232.750	98.050	122.020
Corr	-0.699	-0.708	-0.323	-0.259	-0.260

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 2: Model of number of health care organizations per capita

care organizations being more clustered than would be consistent with the best health outcomes for residents. In section 5 we presented estimates that are consistent with the hypothesis that agglomeration economies are present and of sufficient importance to independently influence the number of health care organizations active in an urban area.

We now seek to estimate the impact of agglomeration on health outcomes in US cities. Again we obtain fixed effects estimates using our panel of data for MSAs from 1989 to 2009. If the agglomeration that reduces individual organization costs also works to improve the quality of health care delivered, then we might hope that a decrease in median distance θ or the presence of clustering $\lambda = 1$ will be associated with a decrease in the mortality rate.

Of course, overall health outcomes depend on many factors. Those that are relatively fixed over time will be captured using the fixed effects estimation technique. We also include controls for the share of the population who are over 65 years of age, the share who identify as black, the share who identify as non-white who are not black, and the overall number of organizations. We include controls for the average surplus revenue (millions of dollars per organization) in the MSA and for the mean inpatient days per admitted patient (as a control both for the general level of health - sicker patients may need to stay longer once admitted - as well as the willingness and ability of local clinics to accommodate longer stays). The results for overall mortality rates are presented in Table 3. Results for similar models applied to mortality rates for cancer, heart disease, strokes, respiratory illness and accidents are presented in the Appendix Tables 4, 5, 6, 7 and 8, respectively.

Table 3 reveals several associations that are not surprising. Age and ethnicity are important determinants of overall health outcomes measured by mortality rates. In addition, an increase in the number of organizations is associated with a decline in the overall mortality rate, consistent with our expectations that overall these organizations are a force for good in the health of the community.

The spatial structure of these organizations, however, is another matter. An increase in the median distance θ between organizations is associated with a significant decrease in mortality from all causes, as suggested in the opening paragraph of section 1. While θ has been rising during the period 1989-2009, the amount of change is very small (about $\frac{1}{6}^{th}$ of a standard deviation). A one standard deviation increase in θ would be associated with a decrease of 3.8 in the annual mortality rate from all causes. Taken over

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			All causes of death		
Median distance	-0.572***	-0.537**	-0.778***	-0.718***	-0.711***
σ	0.215	0.212	0.214	0.213	0.214
Cluster	2.862**	1.864*	1.227	1.492	1.444
σ	1.238	1.093	1.108	1.105	1.107
Organizations	-0.229***	-0.228***	-0.472***	-0.447***	-0.447***
σ	0.033	0.033	0.027	0.026	0.026
Share over 65	3870.902***	3877.081***	3693.780***	3705.160***	3706.477***
σ	72.130	72.100	72.075	72.030	72.137
Surplus revenue	-4.124***	-4.100***	-4.553***	-4.526***	
σ	0.921	0.921	0.934	0.934	
Inpatient days	-1.582***	-1.585***	-0.819***		
σ	0.275	0.275	0.257		
Share Black	114.694***	116.763***			
σ	38.522	38.511			
Share NW, NB	-647.068***	-648.441***			
σ	43.540	43.540			
Peaks	0.203				
σ	0.549				
Gap	-0.254*				
σ	0.150				
Dispersed	3.133*				
σ	1.660				
Constant	405.166***	404.783***	424.044***	414.607***	412.778***
σ	11.375	11.363	9.791	9.337	9.343
R^2 within	0.304	0.304	0.283	0.282	0.280
R^2 between	0.723	0.723	0.641	0.650	0.651
R^2 overall	0.711	0.711	0.632	0.641	0.641
σ_u	96.259	96.278	110.158	108.897	108.793
σ_e	34.401	34.409	34.910	34.931	34.983
ρ	0.887	0.887	0.909	0.907	0.906
F	126.630	127.190	161.940	163.950	163.450
F	409.060	409.060	493.970	590.010	729.460
Corr	0.020	0.020	0.111	0.126	0.127

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 3: Models for death rates due to all causes

all US metro areas this amounts to reduction in deaths of about 9816 per year.

The impact of the index of clustering λ is also striking. In the most complete Model 1, an MSA being clustered is associated with an increase in the mortality rate of 2.86. Given that 62% of US urban areas exhibit clustered health care organizations, this suggests that a change that left health care organizations no more centralized than other non-profit organizations (so that $\lambda = 0$) would be associated with a reduction in annual deaths of about 4584, holding all other factors constant.

While interpreting these models as causal rather than associative is not warranted, the decrease in total deaths numbering 14,400 per year could be said to generate very substantial benefits. Average values for a statistical life in evaluating policies are in the range of $5 million, and if we used this amount the changes would generate benefits of approximately $72 billion dollars per annum.

7 Conclusions and directions for future research

In this paper we have focused on what seems to be a fundamental tension between the economies of agglomeration available to health care organizations and the impacts of concentration of health care organizations on overall health outcomes.

We have identified plausible measures of health care concentration and dispersion, adapted them to the US urban context and calculated values for all US metropolitan areas from 1989 to 1990. We have provided a theoretical framework that can guide our thinking about agglomeration economies and provides a possible test for the existence of important levels of agglomeration economies among US health care organizations. Application of these tests to our data are consistent with the hypothesis of agglomeration economies.

We have collected mortality rates to serve as an indicator of health outcomes, and provided an analysis of the impacts of agglomeration on health outcomes in US cities. This analysis highlights some disturbing results. The analysis suggests that health care organizations in US cities are more clustered than desirable for achieving the best health outcomes. A “back of the envelope” calculation of the economic value of this excessive clustering suggests that a less concentrated location pattern might be associated with 14,400 fewer deaths per year, generating benefits of approximately $72 billion per annum.

Considerable research remains to test the robustness of these results. We are at present involved in extending our analysis in several directions: inclusion of investor-owned hospitals into our data, examination of alternative measures of concentration that weight observations by levels of health care produced, and the use of panel time-series techniques to provide a more direct test of causal links between agglomeration and health outcomes. We hope that these results might provide guidance for improved policies that account for the potential health consequences of health-provider location.

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8 Appendix

The following tables present models estimated using the same variables as those presented in Table 3, but with mortality rates due to individual causes of death rather than for all causes combined.

Table 4: Models for death due to cancer

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Cancer		
Median distance	-0.187**	-0.196***	-0.285***	-0.311***	-0.310***
σ	0.073	0.072	0.072	0.072	0.072
Cluster	-0.674	-0.559	-0.779**	-0.899**	-0.907**
σ	0.419	0.370	0.373	0.373	0.373
Organizations	-0.072***	-0.072***	-0.150***	-0.161***	-0.161***
σ	0.011	0.011	0.009	0.009	0.009
Share over 65	935.205***	935.065***	888.911***	883.807***	884.040***
σ	24.436	24.416	24.294	24.292	24.301
Surplus revenue	-0.694**	-0.694**	-0.791**	-0.803**	
σ	0.312	0.312	0.315	0.315	
Inpatient days	0.004	0.003	0.367***		
σ	0.093	0.093	0.087		
Share Black	-41.829***	-41.618***			
σ	13.050	13.041			
Share NW, NB	-162.376***	-162.357***			
σ	14.750	14.744			
Peaks	0.138				
σ	0.186				
Gap	0.011				
σ	0.051				
Dispersed	-0.114				
σ	0.562				
Constant	104.548***	104.613***	98.425***	102.658***	102.334***
σ	3.854	3.848	3.300	3.149	3.147
within	0.201	0.200	0.184	0.182	0.182
between	0.686	0.686	0.651	0.627	0.628
overall	0.656	0.656	0.620	0.598	0.598
σ_u	26.016	26.009	27.609	28.416	28.394
σ_e	11.654	11.652	11.767	11.780	11.785
ρ	0.833	0.833	0.846	0.853	0.853
F	49.570	49.600	61.370	62.530	62.490
F	170.790	234.840	282.400	334.530	416.230
Corr	-0.031	-0.030	0.115	0.076	0.077

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 5: Models for death due to heart disease

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Heart Disease		
Median distance	-1.053***	-0.947***	-1.678***	-2.178***	-2.178***
σ	0.142	0.141	0.161	0.174	0.174
Cluster	-1.800**	-2.450***	-4.163***	-6.387***	-6.390***
σ	0.821	0.726	0.836	0.900	0.900
Organizations	-0.007	-0.011	-0.582***	-0.793***	-0.793***
σ	0.022	0.022	0.020	0.021	0.021
Share over 65	784.385***	787.037***	537.152***	441.903***	441.982***
σ	47.829	47.881	54.374	58.651	58.647
Surplus revenue	0.329	0.330	-0.043	-0.273	
σ	0.610	0.612	0.704	0.761	
Inpatient days	3.386***	3.400***	6.856***		
σ	0.182	0.182	0.194		
Share Black	-838.332***	-840.529***			
σ	25.543	25.575			
Share NW, NB	-869.359***	-871.114***			
σ	28.871	28.915			
Peaks	-1.512***				
σ	0.364				
Gap	-0.328***				
σ	0.099				
Dispersed	-1.800				
σ	1.101				
Constant	318.241***	316.442***	187.325***	266.314***	266.204***
σ	7.543	7.546	7.386	7.603	7.596
within	0.482	0.482	0.311	0.196	0.196
between	0.043	0.043	0.101	0.040	0.040
overall	0.055	0.055	0.116	0.046	0.046
σ_u	146.272	146.542	77.159	94.118	94.113
σ_e	22.811	22.851	26.337	28.443	28.441
ρ	0.976	0.976	0.896	0.916	0.916
F	70.400	70.480	57.630	50.210	50.220
F	870.210	870.210	564.350	366.560	458.220
Corr	-0.880	-0.880	-0.518	-0.689	-0.689

***** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 6: Models for death due to strokes and related

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			Strokes and Cerebral Atherosclerosis		
Median distance	-0.353***	-0.349***	-0.578***	-0.663***	-0.663***
σ	0.065	0.064	0.068	0.069	0.069
Cluster	-0.401	-0.271	-0.819**	-1.200**	-1.202***
σ	0.372	0.328	0.352	0.356	0.356
Organizations	0.052***	0.052***	-0.135***	-0.172***	-0.172***
σ	0.010	0.010	0.009	0.008	0.008
Share over 65	136.089***	135.870***	41.698*	25.358*	25.413
σ	21.665	21.651	22.907	23.191	23.190
Surplus revenue	0.019	0.017	-0.152	-0.191	
σ	0.277	0.277	0.297	0.301	
Inpatient days	0.152*	0.154*	1.176***		
σ	0.082	0.082	0.082		
Share Black	-200.336***	-200.575***			
σ	11.571	11.564			
Share NW, NB	-329.612***	-329.784***			
σ	13.078	13.074			
Peaks	-0.081				
σ	0.165				
Gap	-0.021				
σ	0.045				
Dispersed	-0.719				
σ	0.499				
Constant	103.088***	102.898***	72.297***	85.848***	85.771***
σ	3.417	3.412	3.112	3.006	3.004
within	0.218	0.218	0.099	0.074	0.074
between	0.062	0.062	0.070	0.038	0.038
overall	0.062	0.062	0.067	0.036	0.036
σ_u	37.133	37.161	19.602	22.329	22.323
σ_e	10.333	10.333	11.095	11.247	11.246
ρ	0.928	0.928	0.757	0.798	0.798
F	27.830	27.870	22.810	23.260	23.400
F	261.770	261.770	136.520	119.150	148.840
Corr	-0.879	-0.879	-0.473	-0.618	-0.617

***** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 7: Models for death due to respiratory illness

	Model 1	Model 2	Model 3	Model 4	Model 5
			Respiratory Illness		
Median distance	0.042	0.031	0.134**	0.263**	0.265***
σ	0.066	0.065	0.067	0.068	0.069
Cluster	1.594***	1.293***	1.516***	2.088***	2.070***
σ	0.381	0.337	0.344	0.354	0.355
Organizations	-0.016	-0.015	0.051***	0.106***	0.106***
σ	0.010	0.010	0.008	0.008	0.008
Share over 65	591.833***	593.787***	603.471***	627.973***	628.459***
σ	22.192	22.205	22.415	23.100	23.146
Surplus revenue	-1.707***	-1.697***	-1.728***	-1.669***	
σ	0.283	0.284	0.290	0.300	
Inpatient days	-1.177***	-1.183***	-1.764***		
σ	0.085	0.085	0.080		
Share Black	216.573***	217.958***			
σ	11.852	11.860			
Share NW, NB	31.473**	31.372**			
σ	13.396	13.409			
Peaks	0.438***				
σ	0.169				
Gap	-0.022				
σ	0.046				
Dispersed	1.894***				
σ	0.511				
Constant	-21.392***	-21.084***	12.732***	-7.587***	-8.262***
σ	3.500	3.500	3.045	2.994	2.998
within	0.216	0.216	0.177	0.123	0.120
between	0.070	0.070	0.421	0.374	0.373
overall	0.067	0.067	0.365	0.310	0.309
σ_u	36.078	36.233	17.445	19.397	19.411
σ_e	10.584	10.597	10.857	11.203	11.225
ρ	0.921	0.921	0.721	0.750	0.749
F	36.330	36.430	34.060	30.790	30.600
F	257.900	257.900	268.250	211.010	254.990
Corr	-0.827	-0.827	-0.418	-0.530	-0.531

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 8: Models for death due to accidents

	Model 1	Model 2	Model 3	Model 4	Model 5
			Accidents		
Median distance	0.154***	0.156***	0.211***	0.244***	0.245***
σ	0.040	0.040	0.040	0.040	0.040
Cluster	0.358	0.271	0.403*	0.550*	0.546***
σ	0.232	0.205	0.207	0.208	0.208
Organizations	-0.010	-0.010	0.035***	0.049***	0.049***
σ	0.006	0.006	0.005	0.005	0.005
Share over 65	25.106*	25.169*	45.798***	52.107***	52.212***
σ	13.529	13.518	13.473	13.535	13.538
Surplus revenue	-0.409**	-0.408**	-0.375**	-0.360**	
σ	0.173	0.173	0.175	0.176	
Inpatient days	-0.197***	-0.197***	-0.454***		
σ	0.052	0.052	0.048		
Share Black	57.663***	57.644***			
σ	7.225	7.221			
Share NW, NB	71.984***	72.065***			
σ	8.166	8.163			
Peaks	-0.028				
σ	0.103				
Gap	0.007				
σ	0.028				
Dispersed	0.296				
σ	0.311				
Constant	22.961***	23.016***	31.850***	26.618***	26.472***
σ	2.134	2.131	1.830	1.755	1.753
within	0.058	0.058	0.036	0.024	0.024
between	0.026	0.026	0.031	0.055	0.055
overall	0.022	0.022	0.010	0.028	0.028
σ_u	11.418	11.411	9.838	10.827	10.830
σ_e	6.452	6.452	6.526	6.564	6.565
ρ	0.758	0.758	0.694	0.731	0.731
F	24.840	24.980	26.940	27.140	27.110
F	57.630	57.630	46.500	37.510	45.820
corr	-0.694	-0.694	-0.545	-0.664	-0.665

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*