Assessing Geographical Clustering of Outpatient Psychiatric Service Utilization in Philadelphia

Naoru Koizumi, PhD*[a], Aileen Rothbard, ScD[b], Amit Patel, MURP[a], Liz Noll MA[b] , Tony E. Smith, PhD[c]

Author Information

* Corresponding Author
School of Public Policy
George Mason University
3401 North Fairfax Drive
Arlington, VA 22201
nkoizumi@gmu.edu
Phone: 703-993-8380
Fax: 703-993-8215

[a] School of Public Policy, George Mason University

[b] School of Medicine, Department of Psychiatry, University of Pennsylvania

[c] School of Engineering, Electrical and Systems Engineering, University of Pennsylvania

Abstract. This study explores a local K-function estimation as a method to identify the spatial clusters of service users of outpatient psychiatric programs in Philadelphia. GIS maps were created to visualize and evaluate the results of K-function analysis. The Medicaid eligible population was used as the control group. The study validated factual information provided in a recent policy brief that reports lower service utilization among African Americans. The subsequent map analysis also indicated that the proximity to service providers and racial composition of the census tract that an eligible individual lives could also affect the decision to be a service user. Specifically, the study found that African Americans living in Caucasian neighborhoods were more likely to be service users while African Americans living in African American neighborhoods were less likely to use services.

Keywords: K-function, Hot-spot, Outpatient psychiatric service utilization, GIS, Racial disparity

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Introduction

During the past several decades, many U.S. states have downsized or closed state mental hospitals. The intention behind this downsizing or closure was to promote social integration of the mentally ill population by replacing the uniform institutional care with a continuum care network in a more community based environment. As part of this movement, CMHC Act (1963) under the Kennedy administration established "Community Mental Health Centers" (CMHCs) across the nation to provide high-quality mental health services that are geographically and economically accessible to service recipients. Each CMHC program is allotted a mutually exclusive "catchment area" with approximately 56,000 to 319,000 residents around its location to offer various outpatient mental health care services. In addition to standard in-patient and out-patient treatment, CMHCs also offer services related to early detection and prevention of the illness. An individual who is in need of these services is, in principle, referred by a case manager to the CMHC program whose catchment area covers his or her residence, although the individual is free to choose any CMHC program.

Despite CMHC's primary goal of providing "accessible" service, our data from Philadelphia suggest that only a fraction of Medicaid eligible population with mental health problems actually utilizes these programs. The primary objective of this study is thus to investigate whether there is any geographical pattern in service utilization and, if so, whether those areas with high service utilization have any distinctive features in terms of geographical access or other hidden social and demographic characteristics such as racial composition or median income level.

The areas with high service utilization are identified using the statistical method known as K-function technique. Originally, K-function was predominantly used in the environmental and natural resources sector to understand, in particular, the spatial pattern of spread of vegetation ([1]). It is relatively recent that the technique started to play a role in social science. In social sciences, this technique has mainly been used to study street crime patterns in urban areas ([2],[3],[4]) or in epidemiological studies to examine the spread of infectious diseases ([5],[6],[7]). Despite that health care accessibility and the equity perspective of it have been popular topics in the services research, a rigorous analysis applying a spatial statistical technique seems to be very rare. To authors' knowledge, a majority of existing literature discusses or conducts either descriptive or non-spatial statistical analysis to examine the accessibility ([8],[9],[10],[11],[12]). The lack of literature is partially due to the fact that a rigorous spatial analysis requires point (i.e., longitude/latitude or address) data of service-users, which are generally tough to access. In addition, a complete dataset of service users is generally difficult to obtain due to the nature of the current U.S. health care system that involves both private and public health care providers. Our study avoids this data challenge by focusing on the population with a serious mental illness whose treatments are generally covered by Medicaid. Specifically, our study identifies the geographical concentrations of CMHC service users using the spatial distribution of the Medicaid eligible population as the controlling point pattern. While this population includes those who do not have a mental illness, our

Philadelphia data suggests that close to 80% of total Medicaid-eligible population is receiving Medicaid assistance for their mental illness.

Method

Our analysis employed the statistical method of local K-functions to detect the spatial local clustering of CMHC service users after controlling for the distribution of Medicaid eligible population. The theory of K-function was standardized by Ripley ([13],[14]) to be applied for the estimation of local clustering. It has been proved to be particularly useful for identifying both the significance and the scale of such clustering with respect to point-source locations ([15],[16],[17]). The specific purpose of the present analysis is to examine whether there are significantly higher rate of CMHC service users than those observed at random when evaluated at the neighborhood of their residences. The local K-function statistics for each location, *i*, is defined by the following equation:

$$(1) \quad \hat{K}_i(d) = \tfrac{1}{\hat{\lambda}} \sum\nolimits_{j \neq i} I_{(d)}(d_{ij})$$

where

d_{ij}: the spatial distance between two events, *i* and *j* (*i.e.*, $d_{ij} = \left| s_i - s_j \right|$),

$$I_{(d)}(d_{ij}) = \begin{cases} 1, (d_{ij} \leq d) \\ 0, \mathit{otherwise} \end{cases}$$

and the sample estimate of clustering intensity is given by

$\hat{\lambda} = \dfrac{N}{a(R)}$, where *a(R)* is area of the study region, i.e., Philadelphia and N is the count of all eligible individuals in the region.

We defined *i* to be the residence location of each service user in the study region. Then, noticing that (1) is simply a count of the number of service users with distance *d* of point *i* scaled by $\frac{1}{\lambda}$, we can calculate the probability values (or p-values) of getting at least as large as the observed count of $m_i - 1$ $(= \sum_{j \neq i} I_{(d)}(d_{ij}) - 1)$ service users when the count of all eligible individuals in *each* distance circle is given by n_i and the count of all service users in the whole region is denoted as N. The exact probabilities are calculated using the Hypergeometric cumulative distribution function (cdf) as:

$$(2) \quad \hat{P}_i(m_i - 1, n_1 - 1, N - 1, n_i) = 1 - \sum_{i=0}^{m_i - 1} \frac{\binom{n_i}{m_i - 1}\binom{N-1-n_i}{n_1 - 1 - m_i - 1}}{\binom{N-1}{n_1 - 1}}$$

Radius of the circle around each service user location used in the analysis was set as ¼ miles after a try-and-error process. The radius was chosen, through visual inspection of the map, to ensure that the radius contains sufficient number of cases to make the statistical test viable and, at the same time, to make sure the circles are small enough to capture local clustering.

The calculation of the p-values was done in MatlabR2000b (MathWorks) and the results were exported to ArcView 9.2 (ESRI) to create the map of Philadelphia with service user clusters. Further visual analyses were conducted by overlaying the locations of service programs and also by comparing the locations of service user clusters with the concentration of African American population and per-capita income measured at the census tract level.

Data Sources and the Study Sample

Two administrative datasets were used in this analysis: 1) Medicaid eligibility data from the Pennsylvania Department of Public Welfare was used to ascertain the Medicaid-eligible population in Philadelphia for 2005 and 2) claims data was used to identify service use for the same period of time from the Community Behavioral Health (CBH) encounter database.

Services for mental health disorders were assessed by the ICD-9 code associated with a primary diagnosis on Medicaid claims for services during 2005 as follows: Schizophrenia (295), Major Depressive Disorder (296.2, 296.3), Bipolar Disorder (296.0, 296.1, 296.4-296.9), and 'Other' Disorders: Psychosis and Neurosis (306-316) and Mental Retardation (317-319), Substance Abuse (291, 292, 303, 304, 305).

Our original study sample consisted of 224,654 Medicaid-eligible adults aged 18 to 64 years who were enrolled in Philadelphia's managed care behavioral health program (CBH) at any time during the 2005 calendar year. Of those, 5,174 records contained invalid addresses for geocoding such as P.O. Box numbers leaving 219,480 individuals with valid addresses for geocoding. However, amongst these, there were 7,399 records which lacked accuracy of addresses due to incomplete (such as absence of house number or street type) addresses or data-entry errors (such as misspelled street-names) and hence couldn't be mapped. Further, Hispanic population (n=35,361) had to be removed from the records due to some reporting problem which resulted in erroneous number of Hispanics treated in the area. The final sample for this study consists of 178,003 adult Medicaid recipients, which represents 79% of the total Medicaid-eligible population in Philadelphia. Of these, 24,062 (13.5%) utilized mental health services during 2005. Consequently, we indentified the 233 outpatient programs that provided services to the users in the sample.

Results

In Figure 1, each dot represents the residence of a service user. The K-function and the associated p-values were evaluated at each of these points. In the map, dark dots indicate lower p-values or cluster of high service utilization ($p < 0.05$) while lighter points represent the lower service utilization area. A visual inspection of the map indicates that there are several "hot-spots" of low utilization as circled in dotted line, including Cobbs Creek, Elmwood, and Kingsessing in Southwest Philadelphia.

[Figure 1 about here]

Figure 2 illustrates the locations of outpatient programs overlaid on the service utilization map that is similar to the one shown in Figure 1. In this map, the p-values evaluated at the service user locations were interpolated using a common interpolation technique known as universal Kriging. The theory of Kriging was originally developed and introduced by Georges Matheron ([18]). The standard books describing the technique include Cressie (1993) ([19]), Waller & Gotway (2004) ([20]) and Bailey & Gatrell (1995) ([21]). Interpolation was necessary for a cosmetic reason, i.e., to make the program locations more discernable on the map. As in Figure 1, the darker area represents clustering of high service use while the areas in lighter colors coincide with lower service utilization. The figure seems to indicate that higher service use tends to be accompanied by the higher number of programs in neighborhood, possibly indicating that low service use is a result of poor geographical accessibility to the programs.

[Figure 2 about here]

Figure 3 presents the residential distribution of African Americans in Philadelphia in 2000. Darker census tracts correspond to a higher percentage of African American residents. Comparison of Figure 2 (or 1) and Figure 3 seems to illustrate that service utilization tends to be low in the areas where the African American population is concentrated. This pattern is particularly evident in Southwest Philadelphia. The comparison also seems to imply that programs are located more dispersedly in African American neighborhoods.

[Figure 3 about here]

In order to further investigate whether the spatial pattern of service utilization differ among African Americans, we conducted an analogous K-function analysis just focusing on African American Medicaid eligible population (n=125,777 or 71% of all eligible population). Figure 4 shows the map of interpolated p-values of service utilization among African Americans evaluated at each African American service user (n = 15,290 or 64% of all service users). The map appears to be almost identical to that shown in Figure 2, implying that, among African American Medicaid eligible individuals, those who live in Caucasian neighborhoods tend to utilize the services, while African American eligible individuals who live in African American neighborhoods tend not to participate in the programs.

[Figure 4 about here]

Results of further statistical analysis revealed that (i) share of Medicaid-eligible African Americans with Supplemental Security Income (SSI) is significantly higher in Caucasian neighborhood (22% vs. 27%, p-value < 0.0005), (ii) Medicaid-eligible African Americans in African American neighborhood are slightly older (36 vs. 35, p-value = 0.0236), and (iii) share of eligible African Americans who are female is significantly higher in African American neighborhood (69% vs. 65%, p-value = 0.0010).

[Figure 5 about here]

Finally, Figure 5 depicts the per-capita income level measured for each census tract. The map exhibits that the census tracts with higher per-capita income seem to correspond to the higher service utilization area in South Philadelphia, while some high service utilization areas seem to exist in the northern part of Philadelphia where per-capita income is not too high. This part of Philadelphia has high concentration of Caucasian residents. Noting that the Medicaid population with mental illness tends to be in similar income-brackets regardless on the census tract they live in, this may indicate that Caucasian eligibles tend to be service users regardless of their income level.

Discussion & Policy Implications

This study revealed areas in the city of Philadelphia where outpatient psychiatric service utilization is unusually low. The visual inspection of the map showing program locations and service use clusters indicated that low service utilization may be attributable to the geographical inaccessibility to service programs. Provider-related policy initiatives in the areas of low service utilization may involve analyses of program capacity, accessibility and possible mismatch between service mix and population needs.

Our map analysis also revealed several racial disparity aspects of the service uses. The service utilization was generally found to be low in the areas with high African American concentration. However, African American eligibles who live in Caucasian neighborhoods tend to utilize services while African American eligibles living in African American neighborhoods tend not to be the service users. The finding in relation to the low service utilization among African Americans coincide with the result of a recent study of adult utilization of public sector behavioral health services in 2005 in Philadelphia that reports African American adults had lower utilization rates in all categories of psychiatric and substance abuse services as well as lower intensity of service use ([22]). In addition to the results related to racial disparity, the study also revealed that Medicaid eligiebles living in the high per-capita income areas tend to use services, although Caucasian eligibles appear to use services regardless of their income level. Patient-related policy initiatives in the areas of low service utilization areas may involve analyses of attitudes toward professional mental health services, cultural beliefs about mental health and targeted outreach services.

Our study has several limitations: First, the control point pattern consisting of the all Medicaid eligible population living in Philadelphia includes those who do not have a mental illness (20% approx.). If the distribution of the eligibles with mental health problems is not completely random, our results of "hot-spots" can be biased. Identifying the reasons of being on Medicaid is however not possible from the data we own. Our main conclusions are less likely to be affected by this limitation, however. For instance, to invalidate the conclusion regarding the low utilization among African Americans to be true, we need to be able to show that eligibles with mental illness are less likely to live in African American neighborhoods. This seems to be an unlikely hypothesis. Similar logic applies to the conclusion about income and proximity to the service providers.

Second, there is a limit in the number of variables we can deal with in the map analysis. In order to measure the impacts of or control the results for other variables available in the data, such as age, gender and detailed diagnosis, we would need to rely on a regression approach. Similarly, our finding related to the positive correlation between geographical proximity to service providers and service use is just one variable in the decision of using or not using the service. The practical decision depends on various other factors such as quality of service providers, existence of family support or other alternatives such as churches, etc. The rigorous analysis to identify the determinants of service use requires additional survey or data collection.

Figure 1. Service Utilization "Hot Spots" for Adult Medicaid Eligible Individuals Treated

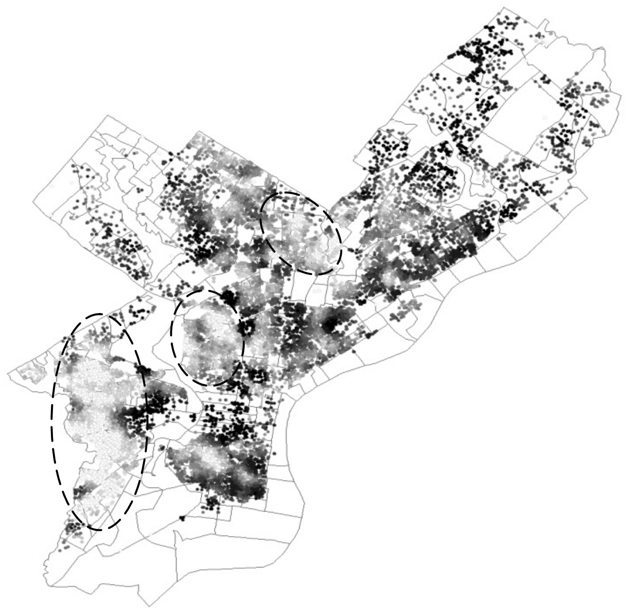


Figure 2. Outpatient Psychiatric Provider Locations overlaid on the Service Utilization Map

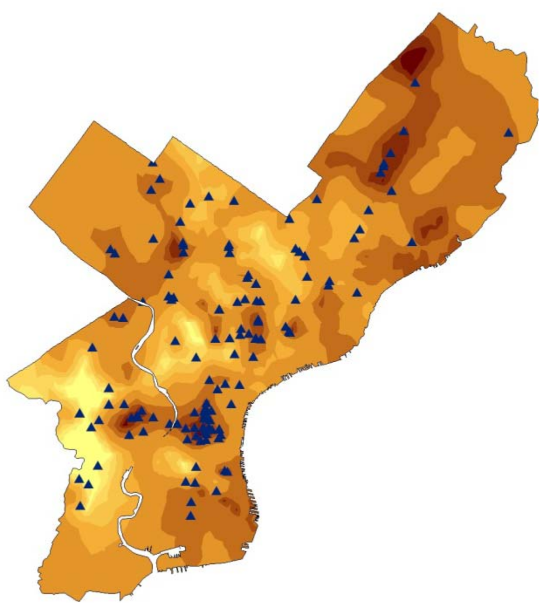


Figure 3. Concentration of African American census population

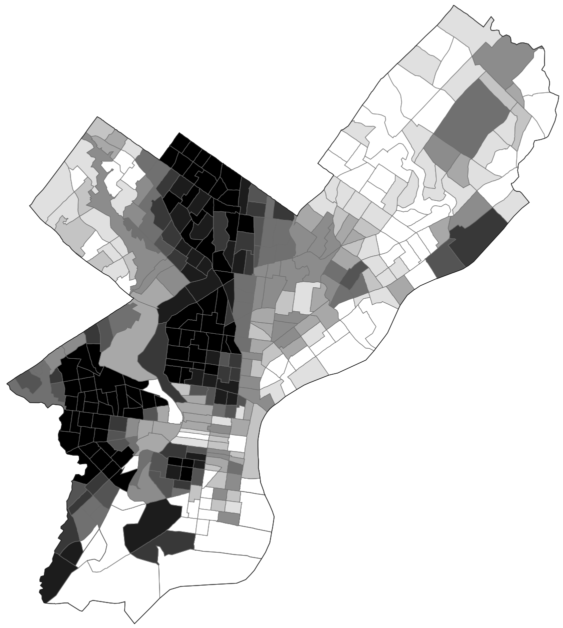


Figure 4. Service Utilization "Hot Spots" for Adult African American Medicaid Eligible Individuals Treated

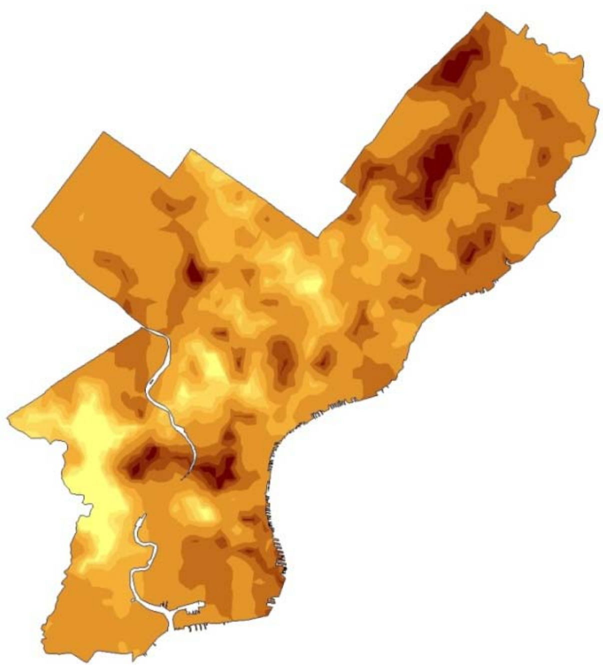
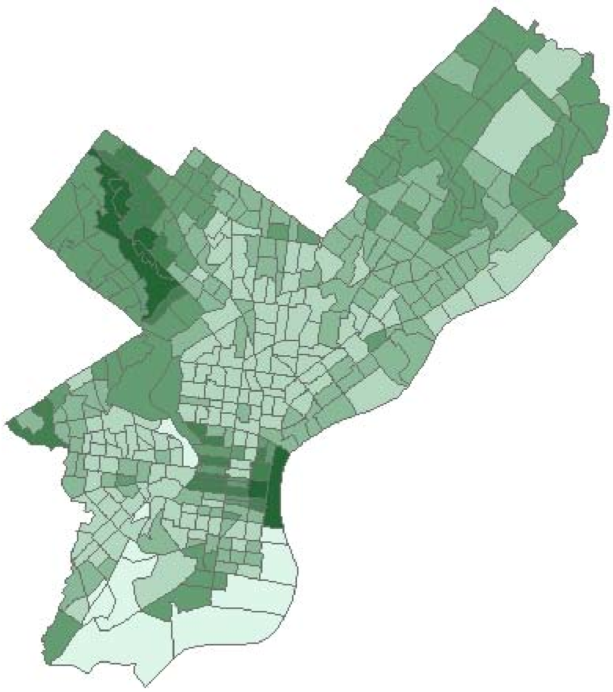


Figure 5. Per-capita Income Level per Census Tract



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