

Creating Peer Groups for Assessing and Comparing Nursing Home Performance

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Given the competitive nature of the healthcare industry, as well as continually rising healthcare costs, administrators of healthcare systems are increasingly interested in evaluating the quality of care provided in their system, as well as the efficiency of resource use. To do these evaluations, administrators often compare quality of care or efficiency of performance across healthcare systems or across units within a single healthcare system. Comparisons across units within a system can be useful in determining where resources should be allocated, where incentives or bonuses might be warranted, or where quality improvement is needed. However, to ensure that comparisons across units are equitable, it is important that the units or facilities that are being compared are similar to one another (peer facilities or peers).

In the research presented here, we consider the identification of peers among nursing home facilities within the Department of Veterans Affairs (VA) healthcare system. We used a methodology that we have previously developed for identification of peers among VA hospitals, modified to accommodate the special characteristics of VA nursing homes.¹ Department of Veterans Affairs nursing homes (VANHs) are quite divergent in their characteristics; thus, it is important that comparable peers be identified for equitable comparisons to be made across facilities. This can be done using a peer grouping methodology. By determining appropriate VANH peers, we can facilitate the equitable benchmarking of nursing homes in areas of quality or financial evaluation and comparisons.

Here we describe our “nearest-neighbor” methodology for developing VANH peer groupings. We then explore the characteristics of the VANH peer groups developed by using the nearest-neighbor methodology and compare them with peer groups developed by using traditional cluster analysis. We emphasize that this methodology is agnostic to healthcare setting (ie, VA vs non-VA) and can be applied to a wide variety of settings.

METHODS

Development of Peer Facilities Using Nearest-Neighbor and Traditional Cluster Methodologies

We included all 130 nursing facilities in the VA in our analyses. To

Background: Publicly reported performance data for hospitals and nursing homes are becoming ubiquitous. For such comparisons to be fair, facilities must be compared with their peers.

Objectives: To adapt a previously published methodology for developing hospital peer groupings so that it is applicable to nursing homes and to explore the characteristics of “nearest-neighbor” peer groupings.

Study Design: Analysis of Department of Veterans Affairs administrative databases and nursing home facility characteristics.

Methods: The nearest-neighbor methodology for developing peer groupings involves calculating the Euclidean distance between facilities based on facility characteristics. We describe our steps in selection of facility characteristics, describe the characteristics of nearest-neighbor peer groups, and compare them with peer groups derived through classical cluster analysis.

Results: The facility characteristics most pertinent to nursing home groupings were found to be different from those that were most relevant for hospitals. Unlike classical cluster groups, nearest-neighbor groups are not mutually exclusive, and the nearest-neighbor methodology resulted in nursing home peer groupings that were substantially less diffuse than nursing home peer groups created using traditional cluster analysis.

Conclusion: It is essential that healthcare policy makers and administrators have a means of fairly grouping facilities for the purposes of quality, cost, or efficiency comparisons. In this research, we show that a previously published methodology can be successfully applied to a nursing home setting. The same approach could be applied in other clinical settings such as primary care.

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Take-Away Points

Comparison of healthcare facilities can be done for assessment of efficiency, as a step in quality improvement, or for resource allocation purposes, to name a few reasons. Our methodology, which results in peer groups of facilities with similar characteristics, is a feasible alternative to classical cluster analysis.

- The results provide managers with a scientific and flexible means of grouping their facilities for comparison purposes.
- This methodology will allow for improved quality, better comparisons of efficiency, and better resource allocation, which will strengthen healthcare reform.

address the widely disparate scales of the measures that we use, all variables are standardized by converting the measure to a *z* score for the population.

With the nearest-neighbor methodology, the software program Clustan (Clustan Software, Edinburgh, UK) was used to calculate the general squared Euclidean distance (GSED) coefficient, which is a multidimensional distance between all pairs of facilities based on the selected variables. Clustan allows for a combination of both continuous and binary measures. The GSED coefficient for the distance between any 2 facilities *j* and *i* is calculated as:

$$d_{ij}^2 = S_k \frac{w_{ijk} (X_{ik} - X_{jk})^2}{S_k w_{ijk}}$$

where x_{ik} is the value of variable *k* in case *i*, and w_{ijk} is a weight of 1 or 0 depending upon whether or not the comparison is valid for the *kth* variable. If differential variable weights are specified, it is the weight of the *kth* variable, or 0 if the comparison is not valid.

We report the Euclidean distance, which is the square root of the GSED.

We identified the facilities most closely surrounding each reference facility in the multidimensional space, providing each facility with a customized group of similar facilities. In this way, there were the same number of peer groups as there were facilities.

For comparison with this methodology, we generated peer groups using a standard 2-stage cluster analysis technique.² We used the same variables and data as in the nearest-neighbor approach. Ward's method of hierarchical clustering was used to generate cluster seeds.³ We then used these seeds as input to the standard k-means iterative algorithm for cluster analysis. Based on the *R*² statistics, which represent the proportion of variation in distance that is explained by the clustering, we elected to create 8 peer groups from the set of VANHs.

There are several differences between peers developed with classical cluster analysis and nearest-neighbor analysis. In classical cluster analysis, membership of a facility in peer groups is mutually exclusive, the size of the peer groups is de-

termined by the results of the clustering, and a facility may be on the "edge" of the sole group that it is in with respect to a certain measure or measures. For example, a facility may have the largest number of beds of any facility in its peer grouping by a substantial margin. Our modification of cluster analysis addressed these concerns. With the nearest-neighbor method, the number

of facilities that were designated as peers to the reference facility were selected depending on the needs of the analysis or comparison. Facilities could and did appear in more than 1 peer grouping, and each facility was by design the hub of its own peer grouping. Finally, the peer relationship was not commutative. If facility B was in facility A's peer group, facility A might or might not have been in facility B's peer group.

Identifying Measures to Use for Peer Groupings

A number of steps, outlined below, were taken to determine which variables to use in developing peer groups for this research. At each step in the process, we took the latest results to a panel of VA nursing home experts who provided feedback on whether our findings and conclusions mapped to their experience and observations.

Step 1. We examined literature on risk adjustment, case-mix reimbursement, determinants of quality of care, and evaluations of quality improvement initiatives.⁴⁻¹⁵ We also queried our expert panel on variables that they viewed as important in categorizing nursing homes into peer groups. We included variables that were related to how many resources would be needed to run the facility or maintain a certain level of quality or treat patients; variables that characterized the facility and gave information about how costly it would be to treat patients there or about the facility's environment; and importantly, variables related to facility characteristics that could not be easily changed by the administrators and affected by patient cost. For example, a care center in an urban area with an academic affiliation would be expected to have higher costs than a small rural facility.

We identified an extensive list of potential measures that might be important in developing peer groupings. These measures fell into the following domains, which we determined were critical for assessing similarities and differences among facilities: size, academic mission, workload/case mix, patient population, and community environment. The expert panel approved the complete list.

Step 2. We narrowed the variables to a working list to use in the peer group algorithm. For this task, we used a combination of technical and practical considerations. We

Table 1. Final Measure Used in the Nearest-Neighbor Modeling for Nursing Home Peer Groupings

Domain	Measure ^a
Size	Number of nursing home operating beds (2)
Academic mission	GRECC status (yes/no) Number of geriatric residents more than 1 (yes/no) (includes geriatric medicine and geriatric psychiatry)
Workload/case mix	Percent census / total stays (3) Percent bed days of care in short-stay skilled treating specialties (4) Percent bed days of care in long-stay dementia and/or psychiatric unit Mean Case Mix Index (5) Percent registered nurse hours / total nursing hours
Patient population	Mean number of activities of daily living (6) Average DxCG ^b patient relative risk score Percent unique patients with Millennium Bill status
Community environment	Urban indicator (2) State-level Medicaid HCBS waiver participants / total number of adults in poverty

GRECC indicates Geriatric Research, Education and Clinical Center; HCBS, Home and Community-Based Services.

^aWeights different from 1 are shown in parentheses.

^bDxCG RiskSmart 2 software (Verisk Health, Salt Lake City, Utah).

gave precedence to variables that were continuous rather than binary or categorical, as continuous variables provide more refined information to use in the algorithm (technical consideration).

Step 3. We considered the availability of each variable, giving preference to more easily obtainable and more frequently updated data (practical consideration).

Step 4. For parsimony in our peer grouping model, we wanted to eliminate variables that did not add new or unique information on the nursing homes. Therefore, we estimated correlations among all of the candidate variables in each domain. Where correlations within a domain were high, we eliminated 1 of the correlated variables (mean correlation [standard deviation] of variables within same domain was 0.283 [0.218]; range, 0.005-0.910). The expert panel approved the reduced list.

Development of Measure Weights for Use in Peer Groupings

To calibrate the relative influence of the various measures, we weighted some of the model variables higher than others before inclusion in the algorithms, with a weight of 1 as the basis point. Selection of the variables to weight higher than 1 was done according to a number of considerations: salience in peer group development or nursing home literature, and information on the importance of the variable provided by our expert panel. The weights greater than 1 that were chosen are shown in **Table 1** in parentheses. These weights ranged from 2, for total operating beds, to 6 for mean activities of daily living (ADLs). The expert panel concurred with the choice of weights.

Exploration of Peer Group Characteristics and Comparison With Traditional Cluster Analysis

We explored the attributes of the peer groups created with the nearest-neighbor methodology and compared them with peer groups formed using traditional cluster analysis. These analyses mirror closely those presented for hospitals as a whole in previous research.¹

Nondiscrete Nature of Nearest-Neighbor Peer Groups. We present nearest-neighbor peer groups for 2 reference nursing facilities (here using 20 VANHs per group) to demonstrate the non-mutually exclusive nature of groups developed with this methodology.

Effect of Number of VANHs in a Peer Group on Distance to Furthest Peer. To explore how the number of VANHs in a peer group affected the Euclidean distance from the reference VANH to furthest peer, we developed 8 sets of peer groups using increments of 5 (ie, 5, 10, 15, ... 40) as the number of VANHs per peer group. We then calculated for each peer group in each of the sets the Euclidean distance from the reference VANH to farthest peer. We present graphically the distribution of these Euclidean distances for each of these sets of peer groups.

Comparison With Traditional Cluster Analysis. We compared the 2 peer grouping methodologies on how diffuse the resulting peer groups were by computing the square root of the sum of squares (RSS) of the Euclidean distances between all pairs of members of the same group, for all peer groups. The RSS of distances is a metric that represents the diffusion of the peer group, with higher values indicating a more diffuse group. We present minimum and maximum RSS of distances across peer groups for the nearest-neighbor groups, as well as

■ **Table 2.** Example of 2 Peer Groupings and the Euclidean Distance From Reference VANH to Each Peer

Peer Rank	Peer Group for Chicago	Euclidean Distance to Peer	Peer Rank	Peer Group for Minneapolis	Euclidean Distance to Peer
1	Minneapolis, MN	1.4781	1	Vancouver, WA	0.34
2	St. Louis, MO	1.4867	2	St. Louis, MO	0.5456
3	Fargo, ND	1.65	3	Boise, ID	0.6733
4	Ann Arbor, MI	1.7451	4	Leavenworth, KS	0.8292
5	Vancouver, WA	1.8554	5	Saginaw, MI	0.8966
6	Oklahoma City, OK	1.9245	6	Ann Arbor, MI	0.9246
7	Tucson, AZ	1.9483	7	Tucson, AZ	0.9655
8	Saginaw, MI	2.1424	8	Grand Island, NE	0.9791
9	Sioux Falls, SD	2.2203	9	Sioux Falls, SD	1.0794
10	Leavenworth, KS	2.5168	10	Roseburg, OR	1.2018
11	Boise, ID	2.5515	11	Dallas, TX	1.2132
12	Grand Junction, CO	2.6634	12	Clarksburg, WV	1.251
13	Dallas, TX	2.6703	13	Manchester, NH	1.2524
14	Cleveland-Brecksville, OH	2.6852	14	Cleveland-Brecksville, OH	1.2682
15	San Diego, CA	2.6963	15	Gainesville, FL	1.2938
16	Grand Island, NE	2.7528	16	Lexington-Leestown, KY	1.3184
17	Manchester, NH	2.8458	17	Oklahoma City, OK	1.3936
18	Clarksburg, WV	2.913	18	Grand Junction, CO	1.3944
19	Spokane, WA	2.914	19	Iron Mountain, MI	1.4493
20	Albuquerque, NM	2.9494	20	Topeka, KS	1.4573

VANH indicates Department of Veterans Affairs nursing home.

the RSS of distance measures for each of the 8 peer groups created using traditional cluster analysis.

RESULTS

Measures Used for Peer Groupings

The final measures that were included in our model are shown in Table 1. Definitions of each of these variables, and data sources for construction of these variables, are shown in the eAppendix (available at www.ajmc.com).

Characteristics of Nearest-Neighbor Peer Groups

Nondiscrete Nature of Nearest-Neighbor Peer Groups. Table 2 shows an extreme example of the non-mutually exclusive nature of the nearest-neighbor peer groups: Minneapolis was the closest neighbor peer for the grouping where Chicago was the reference VANH, but Chicago was not in Minneapolis’s peer group at all. That was because the peer group that had Minneapolis as a reference was much less dispersed than the group for Chicago.

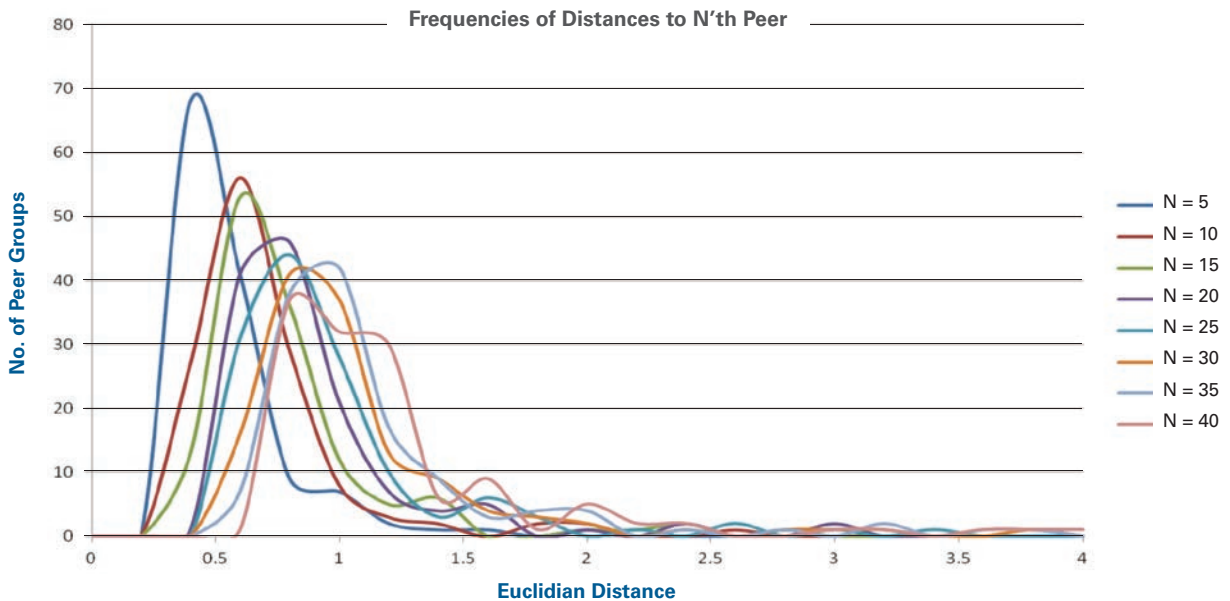
Effect of Number of VANHs in a Peer Group on Distance to Furthest Peer. The Figure shows the distribution of Euclidean distances from the reference VANH to the furthest VANH for

peer groupings of different sizes ($n = 5-40$) for the 130 VANH peer groupings. Using a peer group size of 5, for example, the Figure shows that there is a larger cluster of Euclidean distances from reference VANH to furthest peer at around 0.50, and a long right hand-skewed tail. The concentration of Euclidean distances from reference to furthest peer moves to the right as the number of peers increases; however, it does not move to the right very quickly. The distribution of Euclidean distances for peer groupings with 35 members, for example, shows a concentration only twice that of the groups with 5 members.

Comparison With Traditional Cluster Analysis. Table 3 shows a comparison of the nearest-neighbor peer groupings with peer groupings created by traditional cluster analysis. Because these methodologies are fundamentally different, some of the comparisons were constrained by the methodology. The nearest-neighbor methodology produced 1 peer group for each unique VANH, whereas in traditional cluster analysis the number of groups is determined by the analysis parameters. Also, in nearest-neighbor groupings, the investigator chooses the number of facilities in a group, whereas the cluster analysis itself determines the number of facilities in each grouping, although this can be manipulated by changing analysis parameters.

Creating Peer Groups

■ **Figure.** Distribution of Distances From Reference Nursing Home to Farthest Neighbor in the Peer Group^a



N'th peer indicates farthest neighbor in the peer group.

^aCalculated for 120 peer groups with membership composed of 5 to 40 nursing homes by 5-unit increments.

■ **Table 3.** Comparison of Peer Groupings From Traditional Cluster Analysis and Nearest-Neighbor Analysis, Including Summary Measures for the RSS of Euclidean Distances (Measure of Diffusion)

Measure	Cluster Analysis ^a	Nearest Neighbor ^b
Total number of groups	8 (mutually exclusive)	130 (non-mutually exclusive)
Range, mean, and median number of peers per group	8-31, 16.25, 13.5	Discretionary
RSS across peer groupings	8-member: 6.57	5-member: 0.65, 189.58
	10-member: 7.12	10-member: 1.19, 290.24
For cluster analysis: number in peer group and RSS of group^a	11-member: 9.20	15-member: 1.71, 375.04
	12-member: 6.07	20-member: 2.28, 449.75
For nearest-neighbor analysis: number of members in peer groupings and range of RSS across peer groups with that specified number of members^b	15-member: 8.17	25-member: 2.84, 528.17
	20-member: 8.52	30-member: 3.41, 606.14
	23-member: 12.63	35-member: 4.12, 681.00
	31-member: 17.56	40-member: 4.98, 753.65
Median RSS	8.34	5-member: 2.14
		10-member: 3.54
		15-member: 4.78
		20-member: 6.20
		25-member: 7.61
		30-member: 9.04
		35-member: 10.44
		40-member: 11.81

RSS indicates the square root of the sum of squares.

^aNumber of members in peer group and RSS of peer group

^bNumber of members in peer groupings and range of RSS across peer group

Table 3 also shows how the RSS of distances between members compared between traditional cluster and nearest-neighbor analysis. The nearest-neighbor peer groups showed substantial variation in diffusion at each of the different peer group sizes. For example, when we included 10 facilities in each peer grouping, the RSS ranged from 1.19 to 290.24. At each comparable peer group size, the nearest-neighbor group that was least diffuse was substantially less diffuse than the traditional group of that size; the opposite was dramatically true for a comparison of the most diffuse nearest-neighbor group. For example, when comparing the 20-member groupings, the cluster analysis RSS was 8.52, and the nearest-neighbor groupings ranged from 2.28 to 449.75. When comparing the median RSS between the 2 methodologies, the 3 nearest-neighbor groupings with the most members had greater diffusion than the cluster analysis groupings, whereas the opposite was true for the 5 nearest-neighbor groups with fewer members.

DISCUSSION

In the study by Byrne and colleagues,¹ we described the application of a 2-step process to identify peer groups for medical facilities and applied it to VA medical centers. In the present study, we show how the same technique can be applied to nursing homes. We believe that our method has strong face validity and is practical, because it is grounded in the clinical insights of healthcare providers, uses readily available databases, and applies methodologically sound clustering techniques. We believe that the 2-step methodology described here is generalizable to a wide range of clinical and healthcare settings. No aspect of this process is unique to the VA or to nursing homes. However, it is important that the analyst applying this methodology take the time to determine which attributes of the healthcare setting are most important for grouping the facilities. After that, the healthcare system that wants to implement this methodology must have the data that are needed to adequately describe the facilities of interest. When these 2 steps are successfully taken, this technique (1) can be applied to any large collection of medical facilities (eg, outpatient clinics) in which there is sufficient diversity that they cannot accurately be compared as a homogeneous group and (2) can be used, for example, to compare the facilities on the basis of efficiency, cost, or other outcome measure. It can also be used to look for problem areas in quality of care (ie, to determine whether patients are at greater risk in facilities with certain characteristics).

In this study, we also explored the characteristics of the nearest-neighbor groups that we developed and compared them with traditional cluster analysis. We found that the

nearest-neighbor peer groups were less diffuse than those developed with traditional cluster analysis. In addition, the Euclidean radius distances of the peer groups showed a right-skewed distribution for a range of peer group sizes, and the high point of the distribution did not move substantially to the right as the number of facilities in a peer group increased. If tight-knit clusters are a desirable trait for peer groups, then researchers and policy makers should consider a nearest-neighbor approach when developing peer facility groupings.

Increasingly, healthcare providers are being compared based on quality, efficiency, and finances. These decisions are being made across a wide range of healthcare service providers. For example, the Hospital Compare website provides information that allows consumers to directly compare performance measures across multiple hospitals.¹⁶ For such comparisons to be fair and to secure buy-in by facility leaders and staff, providers must be compared with their peers, and careful consideration of who are truly “peers” is essential.

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■ eAppendix. Data Sources and Variable Definitions

Data Sources

We obtained data on facility, patient, and community characteristics from the following sources:

- VA National Patient Care Database (Extended Care Inpatient Files)
- VISN Service Support Center (VSSC) and Bed Control Data / Workload Data
- DxCG relative risk scores (Diagnostic Cost Group method of risk adjustment)
- Minimum Data Set Survey (VA nursing homes)
- VA Office of Academic Affiliations Residents List

Definitions of Final Measures

Size

(1) Nursing home operating beds. The number of CLC operating beds was obtained from Bed Control Data File. (For 2 facilities, we obtained bed data directly from the site administrators.)

Academic mission

(2) Geriatric Research, Education and Clinical Center (GRECC) status (yes/no). GRECC status is a binary indicator noting presence of a specialized GRECC program. The GRECCs are “centers of geriatric excellence” designed for the advancement and integration of research, education, and clinical achievements in geriatrics and gerontology into the total VA healthcare system.”

(3) Number of geriatric residents more than 1.0 (yes/no). A binary indicator noting the CLC has more than 1.0 geriatric residents/fellows.

Workload/case mix

(4) Percent census/total stays. This measure serves as an indicator of turnover in the facility.

FY09 inpatients on 9/30/09 (census stays) / (# FY09 discharges + FY09 census stays)

(5) Percent days of care in short-stay skilled treating specialties. The percentage of all FY09 days of care (discharges + census stays) delivered in short-stay skilled treating specialties.

(6) Percent long-stay dementia and/or psych days. The percentage of all FY09 days of care (discharges + census stays) delivered in long-stay dementia and/or psychiatric care treating specialties. The expert panel suggested inclusion of this variable, as the acuity of these patients may not be properly represented in the Case Mix Index (CMI) from the Minimum Data Set.

(7) Mean CMI. This measure reflects a combination of patient characteristics and treatment intensity. To develop a facility-level metric, we identified all full assessments in the FY09 MDS data as those with:

- Primary reason for assessment is (1) admission assessment (required by day 14); (2) annual assessment; or (3) significant change in status assessment (2 or more activity of daily living [ADL] areas); OR
- Primary reason for assessment is “none of the above” and patient has been given a Medicare 5-day assessment.

For each CLC we calculated the mean CMI value for each month of FY09 and then averaged across all months.

(8) Percent RN hours /total nursing hours. This measure is meant to capture patient complexity and severity of case mix for the CLC.

Total RN hours/(RN + LVN + nurse assistant hours)

For each CLC we calculated the mean percent RN hours for each month of FY09 and then averaged across all months.

Patient population

(9) Mean ADL Index. This measure is intended to reflect the functional status of patients being served by a CLC. To develop a facility-level metric, we identified all full assessments as with the mean CMI measure (see above). For each CLC we calculated the mean ADL value for each month of FY09 and then averaged across all months.

(10) Average Patient Relative Risk Score (RRS). This is the average of a facility's patient-level relative risk scores, a measure of overall patient illness burden. The individual patient's DxCG RRS is a ratio of predicted costs based on diagnoses to average observed costs:

We derived diagnostic cost group (DCG)-based RRSs from the Houston HSR&D VA DCG model for users in priority groups 1-8, then calculated and scaled these RRSs across the VA to yield a population mean of 1. We used DxCG RiskSmart 2.3 software.

The average RRS at a facility is the sum of RRSs of all patients at that facility divided by the number of unique patients at the facility in FY 2009. A RRS value of 1.00 reflects an average illness burden of the national VA population.

(11) Percent FY09 unique patients with "Millennium Bill" status. This variable is the percent of unique patients at the CLC with service connection status $\geq 70\%$.

Community environment

(12) Urban status (yes/no). This measure identifies a CLC as "urban," where urban indicates the CLC is located in a county within a metropolitan area of population equal to 250,000 or more in 2003. This threshold was determined by applying the

USDA Economic Research Service Rural Urban Continuum codes, letting urban = (1, 2).

(13) Ratio of Medicaid Home and Community-Based Services (HCBS) waiver participants / total adults in poverty. We identified the number of Medicaid HCBS waiver participants for each state, excluding those for children and mental retardation/developmental delays, and divided by the total number of adults in poverty for that state. This is a measure of alternative resources for low-income, frail veterans (Kaiser Commission on Medicaid and the Uninsured, 2009).