Variation in Patient-Sharing Networks of Physicians Across the United States

Bruce E. Landon, MD, MBA
Nancy L. Keating, MD, MPH
Michael L. Barnett, MD
Jukka-Pekka Onnela, PhD
Sudeshna Paul, PhD
A. James O'Malley, PhD
Thomas Keegan, PhD
Nicholas A. Christakis, MD, PhD

Context Physicians are embedded in informal networks that result from their sharing of patients, information, and behaviors.

Objectives To identify professional networks among physicians, examine how such networks vary across geographic regions, and determine factors associated with physician connections.

Design, Setting, and Participants Using methods adopted from social network analysis, Medicare administrative data from 2006 were used to study 4 586 044 Medicare beneficiaries seen by 68 288 physicians practicing in 51 hospital referral regions (HRRs). Distinct networks depicting connections between physicians (defined based on shared patients) were constructed for each of the 51 HRRs.

Main Outcomes Measures Variation in network characteristics across HRRs and factors associated with physicians being connected.

Results The number of physicians per HRR ranged from 135 in Minot, North Dakota, to 8197 in Boston, Massachusetts. There was substantial variation in network characteristics across HRRs. For example, the mean (SD) adjusted degree (number of other physicians each physician was connected to per 100 Medicare beneficiaries) across all HRRs was 27.3 (range, 11.7-54.4); also, primary care physician relative centrality (how central primary care physicians were in the network relative to other physicians) ranged from 0.19 to 1.06, suggesting that primary care physicians were more than 5 times more central in some markets than in others. Physicians with ties to each other were far more likely to be based at the same hospital (69.2% of unconnected physician pairs vs 96.0% of connected physician pairs; adjusted rate ratio, 0.12 [95% CI, 0.12-0.12]; $P<.001$), and were in closer geographic proximity (mean office distance of 21.1 km for those with connections vs 38.7 km for those without connections, $P<.001$). Connected physicians also had more similar patient panels in terms of the race or illness burden than unconnected physicians. For instance, connected physician pairs had an average difference of 8.8 points in the percentage of black patients in their 2 patient panels compared with a difference of 14.0 percentage points for unconnected physician pairs ($P<.001$).

Conclusions Network characteristics vary across geographic areas. Physicians tend to share patients with other physicians with similar physician-level and patient-panel characteristics.

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In 1973, Wennberg and Gittelsohn[1] first described the extent to which local practice patterns varied across towns in Vermont. Decades of subsequent research demonstrating both small- and large-area variations in care suggest that local norms play an important role in determining practice patterns and that, in aggregate, such norms and customs might account for a large proportion of the variability that exists in health care.[2-4] Whatever the exact cause, small-area variations in patterns of care suggest that physicians may come to conform to the behavior of other nearby physicians.

This might happen in part by physicians actively sharing clinical information among themselves through informal discussions and observations (eg, of patient records) that occur in the process of providing care to shared patients.[5] These informal information-sharing networks of physicians differ from formal organizational structures (such as a physician group associated with a health plan, hospital, or independent practice association) in that they do not necessarily conform to the boundaries established by formal structures. However, formal organizational affiliations clearly influence the interactions physicians have. Informal information-sharing networks among physicians may be seen as organic or natural rather than as artificial or deliberate.

The potential influence of informal networks of physicians on decision making has been understudied despite the potential importance of these networks in day-to-day practice. In addition, understanding more about physicians' predilections to form relationships with colleagues could be im-

For editorial comment see p 294.

Author Affiliations: Department of Health Care Policy, School of Medicine (Drs Landon, Keating, Barnett, Paul, O'Malley, Keegan, and Christakis), Department of Biostatistics, School of Public Health (Dr Onnela), and Department of Sociology, Faculty of Arts and Sciences (Dr Christakis), Harvard University, Cambridge and Boston, Massachusetts; Division of Primary Care and General Internal Medicine, Department of Medicine, Beth Israel Deaconess Medical Center, Boston, Massachusetts (Drs Landon and Christakis); and Division of General Internal Medicine, Department of Medicine, Brigham and Women's Hospital, Boston, Massachusetts (Drs Keating and Barnett).
Corresponding Author: Bruce E. Landon, MD, MBA, Harvard Medical School, 180 Longwood Ave, Boston, MA 02215 (landon@hcp.med.harvard.edu).

Box. Glossary of Network Terms

Betweenness centrality: how central a node (or a physician) is within his/her network, obtained by considering the shortest paths from each node to every other node in the network (FIGURE 1).

Relative betweenness centrality: the mean betweenness centrality of one physician type (eg, primary care physician) relative to all other physicians in the network.

Bipartite network: bipartite refers to a network in which the nodes can be partitioned into 2 sets, physicians and patients, such that all ties link nodes from 1 set to the other and there are no ties within a set. We converted this to a unipartite network of linked physicians.

Clustering coefficient: the proportion of network neighbors of a node that is directly connected to one another, thus, a proportion of physician's colleagues who share patients with one another.

Connection, edge, or tie: a tie connects 2 nodes, in this case, linking 2 physicians in the network who share patients as identified in Medicare claims data. Connections likely correspond to information-sharing relationships between physicians.

Degree, adjusted degree: the number of ties a given node has; thus, the number of physicians a physician is connected to through patient sharing. Because patient volume influences the number of connections, we obtained an adjusted degree by dividing degree by the total number of Medicare patients the physician shares with all other physicians.

Homophily: the tendency of individuals with similar characteristics to associate with one another.

Node or actor: an individual actor or agent in the network, in this case a physician.

Shared patients: the total number of shared patients across all ties for an individual physician.

Social network: a set of actors, in this case physicians, and a set of relationships linking the actors together. Social networks can be used to study the structure of a social organization and how this structure influences the behavior of individual actors.

portant for identifying levers to influence how physicians exchange information with one another. Herein, we discuss the use of novel, validated methods from social network analysis to define professional networks based on patient sharing among physicians, and examine how such networks vary across geographic areas. We also identify physician and patient population factors that are associated with patient-sharing relationships.

METHODS

Sharing of patients based on administrative data can identify information-sharing ties among pairs of physicians.[6] Physician encounter data from the Medicare program were used to define networks of physicians based on shared patients.[7] A social network is defined as a set of actors and the relationships or connections that link these actors together (BOX). Social network analysis can be used to study the structure of a social system and to understand how this structure influences the behavior of constituent actors. In this study of physician patient-sharing networks, nodes represent the individual physicians in the network and ties (or edges) represent shared patients between nodes. The presence of shared patients was used to infer information-sharing relationships between 2 physicians. Ties vary in their weight according to the number of shared patients, with more shared patients implying stronger connections between physicians.[6] This study was approved by the Harvard Medical School institutional review board, which also approved a waiver of consent for participants in the study.

Identifying the Sharing of Patients

Shared patients were identified using Medicare claims from 2006. To maximize data on shared patients among physicians practicing in local areas, we obtained data for 100% of Medicare beneficiaries (including those aged <65 years) living in 50 market areas (defined as hospital referral regions [HRRs]) randomly sampled with probability proportional to their size; this was the maximum amount of data that the Centers for Medicare & Medicaid Services would release to us. The HRRs represent regional markets for tertiary care, which were defined based on referral patterns for cardiovascular and neurosurgical procedures performed.[8] In addition, the Boston HRR was included to aid in the development and testing of the methods of the study because it is familiar to us. We included patients enrolled in both Medicare Parts A and B and excluded patients enrolled in Medicare Advantage plans, for whom encounter data were not available.

Encounters with physicians were defined based on paid claims in the carrier file. We excluded claims for specialties in which physicians were not involved in direct patient care or were not selected specifically (eg, radiology, anesthesia). We identified all evaluation and management services, and also included procedures with a relative value unit of at least 2.0 to capture surgical procedures that are often reimbursed via bundled fees that include preprocedure and postprocedure assessments. We excluded claims for laboratory and other services not requiring a physician visit and claims generated from physicians who saw fewer than 30 Medicare patients during 2006 or who practice outside of the included HRRs. Although the latter exclusions increase the risk of excluding physicians who work on the geographic boundary of a HRR, information on these physicians would have been incomplete.

Characteristics of Physicians and Patients

Physician characteristics including age, sex, medical school, and place of residency were defined using data from the

American Medical Association's Physician Masterfile.[9] Billing zip code and specialty designations from Medicare claims (defined based on the plurality of submitted claims) were used to assign a principal specialty and practice location. Physicians (<1%) for whom we could not identify a practice location or dominant specialty were excluded. Physicians were classified as primary care physicians (PCPs; included: general internists, family practitioners, and general practitioners), medical specialists, or surgical specialists.

For each physician, we calculated the following practice-level variables for their Medicare patients: mean age, percentage of females, race/ethnicity (percentage of whites, blacks, and Hispanics), and mean health status measured using the Centers for Medicare & Medicaid Services' Hierarchical Condition Categories risk adjustment model.[10] Each physician's practice style was characterized based on the intensity of care delivered to his/her patients measured using Episode Treatment Group software.[11] Intensity of care was defined based on the mean resource use for episodes of care delivered by that physician compared with similar episodes delivered by all of the other physicians (eAppendix and eTable at http://www.jama.com). A physician with an intensity index of 1.0 delivers care for all the conditions he/she treats that is equal to the intensity (as measured by total service use) of the average physician of the same specialty treating those conditions. A score of 1.2 would indicate that he/she is 20% more costly.

Constructing Physician Networks

Physician networks were discerned from a patient-physician bipartite or 2-mode network. The term *bipartite* means that nodes in the network can be partitioned into 2 sets (eg, physicians and patients) and that all relationships link nodes from 1 set to the other.[12] A unipartitite (physician-physician) network[13,14] was formed by connecting each pair of physicians who shared patients with one another, and a weight was assigned to such ties based on the number of patients shared (Figure 1). A key decision involved determining the minimum number of shared patients that could optimally be used to define connections representing important relationships. We previously found (using these same Medicare data) that physicians in a single academic health care system who shared 8 or more patients had an 80% probability of having a validated information-sharing relationship.[6] This threshold might differ depending on specialty and the clinical activity of each physician.

We explored both absolute thresholding (using the same threshold for each physician and specialty) and relative thresholding (creating a customized threshold for each physician). We found that using a relative threshold that maintained the strongest 20% of ties for each physician appeared to best maintain intrinsic network characteristics while also eliminating noise that might result from spurious connections. Although this method likely eliminated some ties that represent true relationships, it maintains the strongest ties for each physician and therefore maintains the relationships likely to be most influential to that physician. In sensitivity analyses, using the top 10% and 30% of ties, our main results were similar (eAppendix).

Network Descriptive Measures

The networks were described after applying our thresholding procedure and by focusing on a set of measures applicable across all types of physicians: adjusted physician degree, number of patients shared by the physician, relative betweenness centrality, and physician-level clustering coefficient (Figure 1 and Box).

Degree was defined as the number of physicians connected to a given physician through patient sharing. Because the number of connections was influenced by patient volume, we adjusted the degree by dividing each physician's degree by the total number of Medicare patients that the physician shared with other physicians (adjusted degree). Thus, physicians with a higher degree were connected to and shared patients with more physicians. The number of shared patients was defined as the total number of shared patients across all ties for a physician and reflects the number of patients that physician cared for, as well as his/her tendency to share care with other physicians. The betweenness centrality of a physician represented how central a physician was within his/her network of colleagues.[14-16]

To calculate relative betweenness centrality for PCPs or medical specialists in each HRR-level network, mean PCP or specialist centrality for that network was first calculated and then later divided by the mean centrality of all other physicians in the network. Central physicians in a network are likely to have more influence. The clustering coefficient of a physician in the network refers to the proportion of a physician's colleagues who also shared patients with one another. A physician could share patients with 10 other physicians, none of whom share patients with each other, or a physician could share patients with 10 other physicians, all of whom were interconnected. A network with a high-clustering coefficient was more densely connected.

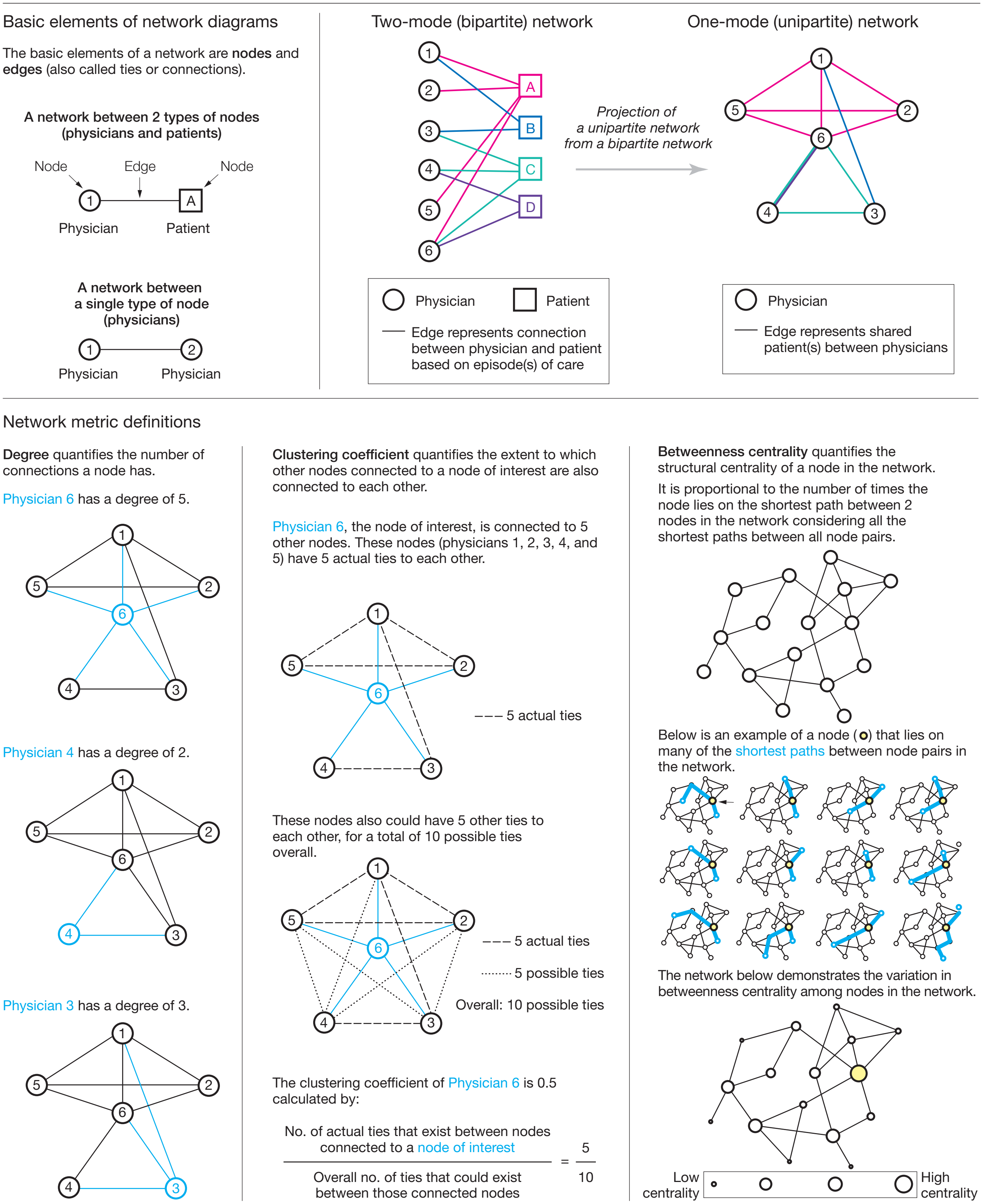
For descriptive purposes, each physician was assigned to a principal hospital based on where they filed the plurality of inpatient claims or, if they did not do inpatient work, to the hospital where the plurality of patients they saw received inpatient care.[17]

Statistical Analyses

The networks in each of the 51 HRRs were first characterized. Selected networks were visualized using the Fruchterman-Reingold algorithm.[18] Unadjusted differences in network measures across regions were assessed using 1-way analysis of variance.

To examine factors associated with the existence of ties between physicians, we first compared the characteristics of pairs of connected physicians within each of the regions with the characteristics of all other potential pairs for

Figure 1. Basic Social Network Concepts



which there was no connection. These analyses included all physicians and ties (not just the 20% of strongest ties used for the descriptive network analyses). For each physician pair, whether connected or not, difference measures were defined for each of the main independent variables of interest. For instance, distance was defined as the number of kilometers between the zip code centroid for each pair's office addresses (and was log-transformed to limit the effect of outliers). Shared patients were excluded from the calculation of patient-panel attributes for each physician pair, so the results are not inflated by the fact that shared patients have identical characteristics.

Bivariate differences were evaluated using 2-sided *t* tests or χ^2 tests (as appropriate) and were considered significant if the *P* value was less than .05. Because our analyses are hypothesis-generating, we did not adjust *P* values for multiple comparisons. We then estimated univariable and multivariable models to identify characteristics associated with having a tie and increasing tie strength between 2 physicians within the network (ie, the extent to which characteristics of 2 physicians connected to each other are similar, also known as homophily). The dependent variable was the number of shared patients between any pair of physicians and the predictors were the difference measures. Because the prevalence of potential ties with 0 patients was large, we found that a negative binomial distribution best fit the data.

To make the results easier to interpret, regression coefficients were converted to standard rate ratios because the outcome is not binary. For the differences in patient characteristics measured as percentages, we present rate ratios representing the increase in the number of ties for each 10% difference in a patient population characteristic across the 2 physicians. All analyses were performed with SAS version 9.2 (SAS Institute Inc).

RESULTS

We studied 4 586 044 Medicare beneficiaries from 51 HRRs who were seen by 68 288 physicians. The randomly sampled HRRs are distributed across all regions of the country and include urban and rural locations (eFigure 1 at http://www.jama.com). The characteristics of all included physicians and patients are presented in TABLE 1. The mean physician age was 48.8 years and about 80% were male. Among the Medicare patients, the mean age was 71 years and 40% were male. The distribution of the number of shared patients between linked physicians for the entire data set is depicted in eFigure 2.

After applying the relative thresholding rule (keeping only ties with strength in the top 20th percentile for each physician), the mean number of patients shared per 100 Medicare ben-

Table 1. Characteristics of Physicians, Patients, and Networks Stratified by Hospital Referral Region

Characteristics	Mean (SD) [Range]	Hospital Referral Region: Boston, MA	Minot, ND	Joliet, IL	Miami, FL
Physicians					
No.	1339 (1621) [135-8197]	8197	135	496	3600
Age, y	48.5 (1.3) [46.1-51.7]	48.3	48.1	46.3	51.7
Males, %	80.3 (4.9) [69.2-89.7]	70.1	82.4	77.8	84.1
Type of practice, %					
Primary care	41.9 (5.4) [27.6-53.3]	38.5	50.4	40.1	39.0
Medical specialist	30.0 (4.8) [20.7-47.1]	36.8	20.7	33.5	35.7
Surgical specialist	28.0 (3.3) [21.3-35.5]	24.7	28.9	26.4	25.2
Patients					
No.	279 (84) [126-447]	224	260	317	228
Whites, %	86.6 (11.5) [49.4-98.8]	89.1	92.7	89.4	61.7
Blacks, %	8.9 (10.1) [0.1-42.1]	6.2	0.2	8.7	111.9
Hispanics, %	1.8 (4.0) [0-24.2]	1.5	0	0.9	24.2
Females, %	59.9 (2.0) [54.4-64.2]	60.8	58.0	61.6	61.1
Medicaid, %	23.0 (10.0) [7.7-51.9]	27.7	12.0	14.7	51.9
Age, y	70.7 (1.6) [67.1-74.6]	70.8	73.2	71.4	71.6
Hierarchical clinical condition score	1.9 (0.3) [1.5-2.8]	2.2	1.7	2.0	2.8
Episode treatment group intensity score	1.03 (0.06) [0.9-1.2]	1.1	1.2	1.0	1.1
Networks					
No. of ties	50 927 (75 963) [1568-392 582]	392 582	1568	12 914	218 136
Adjusted degree[a]	27.3 (10.4) [11.7-54.4]	51.4	11.7	18.6	54.4
No. of shared patients	852 (336) [297-1504]	835	498	1222	1146
Clustering	0.55 (0.06) [0.40-0.67]	0.48	0.67	0.62	0.47
Relative centrality					
Primary care physician	0.38 (0.17) [0.19-1.06]	0.52	0.41	0.19	0.46
Medical specialist	3.47 (1.33) [0.48-7.40]	1.62	5.59	3.98	2.12

[a] Indicates the number of other physicians each physician was connected to per 100 Medicare beneficiaries across all hospital referral regions.

eficiaries across the entire sample was 27.3. Network attributes are depicted graphically in eFigure 3, which shows scatter plots of the network topological characteristics of interest vs the network size for the included HRRs. The network measures fall into 2 distinct categories: those with a strong dependence on network size (adjusted degree, clustering, number of shared patients) and those less associated with network size (relative PCP and medical specialist centrality).

Network characteristics across the geographic regions also are shown in Table 1. Substantial variation was observed across HRRs. For example, the number of included physicians ranged from 135 in Minot, North Dakota (1568 ties) to 8197 in Boston, Massachusetts (392 582 ties). Physician-adjusted degree is much higher in Boston (the average physician was connected to 51.4 other physicians per 100 Medicare patients cared for in Boston vs 11.7 in Minot), whereas clustering is greater in Minot (0.62 in Minot vs 0.48 in Boston; the clustering coefficient ranges from 0-1 and quantifies the proportion of physicians who, in addition to being connected to a given physician, are also connected to one another).

As noted above, these network characteristics also were strongly associated with network size. Other variation cannot be explained by the general relationship to network size, however, such as the greater relative betweenness centrality of specialists in Minot vs Boston (specialists are >5 times more central than PCPs in Minot, whereas in Boston, they are only 1.6 times as central), meaning that certain structural aspects of physician networks are not simply functions of network size.

Graphical depictions of networks for 2 HRRs are presented in **FIGURE 2**. Networks are pictorially represented using spring embedder methods, which position objects with stronger connections (ie, physicians with more shared patients) in closer physical proximity within the network (Figure 2A and online interactive showing variations in network configurations). In Minneapolis/St Paul, Minnesota, there are many ties between physicians in different hospitals, with primary care physicians centering their patient sharing around a pool of medical and surgical specialists in multiple hospitals. Thus, although physicians are clustered according to their principal hospital affiliation, the close proximity of the clusters is indicative of multiple ties across hospitals. Alternatively, in Albuquerque, New Mexico, network connections are mostly confined within hospitals, and connections are generally confined to their hospital. Consequently, the hospital clusters in Albuquerque are more distinct and separated in space.

Factors Associated With Network Ties

Among all physicians and ties (rather than just the 20% of strongest ties) across the 51 HRRs, male physicians were more likely to have ties with other male physicians (65.1% of connected physician pairs were male-male vs 54.6% of unconnected physician pairs, $P < .001$), but female physicians were less likely to have ties with other female physicians (3.8% of connected physician pairs vs 6.4% of unconnected physician pairs, $P < .001$) (**TABLE 2**). Physicians with ties were also closer in age (mean difference of 11.5 years for those with ties vs 12.5 years for those without ties, $P < .001$).

Patterns varied by physician specialty as well. Physicians with ties to each other were far more likely to be based at the same hospital (69.2% of unconnected physician pairs vs 96.0% of connected physician pairs; adjusted rate ratio, 0.12 [95% CI, 0.12-0.12]; $P < .001$). Connected physician pairs also were more likely to be in close geographic proximity. The mean distance for connected pairs was 21.1 km vs 38.7 km for unconnected pairs ($P < .001$). Connected physicians also had more similar practice intensity as measured by episode treatment groups[11] (a difference of 0.29 for linked physicians vs a difference of 0.31 for unlinked physicians, $P < .001$).

Characteristics of physicians' patient populations also were associated with the presence of ties between physicians. Across all racial and ethnic groups, connected physicians had more similar racial compositions of their patient panels (net of any shared patients) than unconnected physicians. For instance, connected physician pairs had an average difference of 8.8 points in the percentage of black patients in their 2 patient panels compared with a difference of 14.0 percentage points for unconnected physician pairs ($P < .001$). Similarly, differences in mean patient age and percentage of Medicaid patients also were smaller for connected physicians than unconnected physicians. Medical comorbidities (measured by the Hierarchical Condition Categories score) were also more similar, suggesting that connected physicians had more similar patients in terms of clinical complexity than unconnected physicians. All of these results were confirmed in multivariable regression models (Table 2).

Physicians thus tend to cluster together along attributes that characterize their own backgrounds and the clinical circumstances of their patients. We observed similar patterns when repeating the analyses using logistic regression after applying the thresholding criteria.

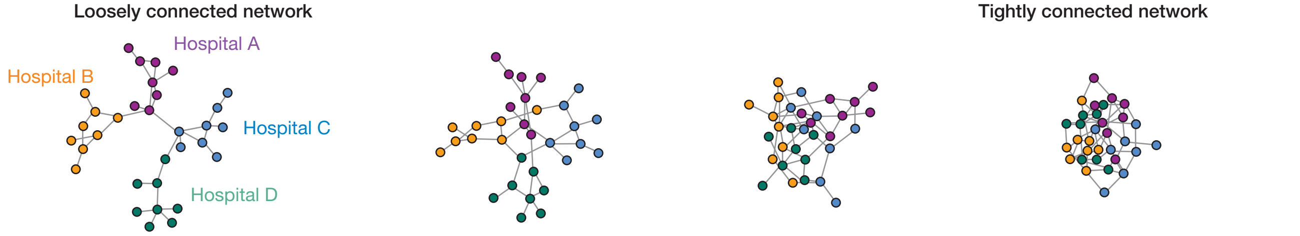
COMMENT

Our results demonstrate substantial variation in physician network characteristics across geographic areas in terms of both topological features and dyadic ties, even for networks of generally similar size. It has long been known that physician behavior varies across geographic areas, yet our understanding of the factors that contribute to these geographic differences is incomplete.[1] Our findings suggest that variation according to network attributes might help explain health care variation across geographic areas, particularly given what is known about how networks function. However, additional studies are needed to ascertain the extent to which the structural variation in physician interactions—on both macro and micro scales—can help explain variation in medical practice across geographic areas.

Our results show that physicians tend to share patients with colleagues who have similar personal traits, practice styles, and patient panels, although the influence of some of these traits is small in magnitude. Working at the same primary hospital and having similar sociodemographic characteristics among patients in their patient

Figure 2. Examples of Variations in Patient-Sharing Physician Networks

A Variations in network configurations based on the number of patient-sharing connections between physicians at different hospitals

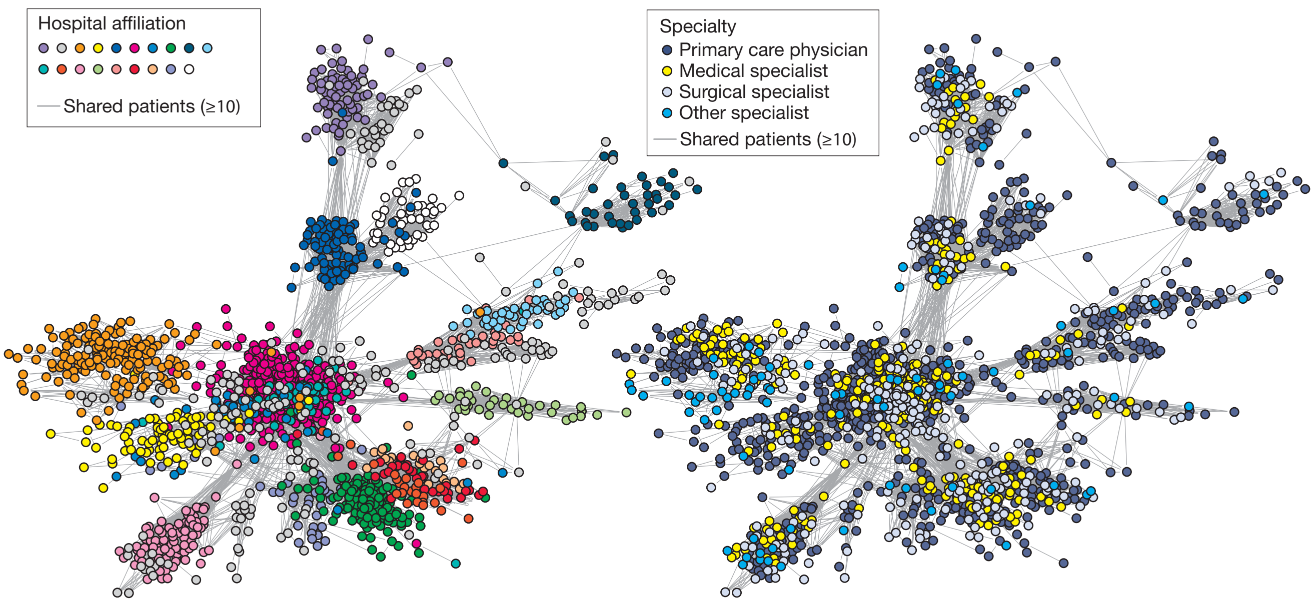


In a network in which physician connections are mostly within hospitals, the network has tight hospital clusters but loose connections between hospital clusters.

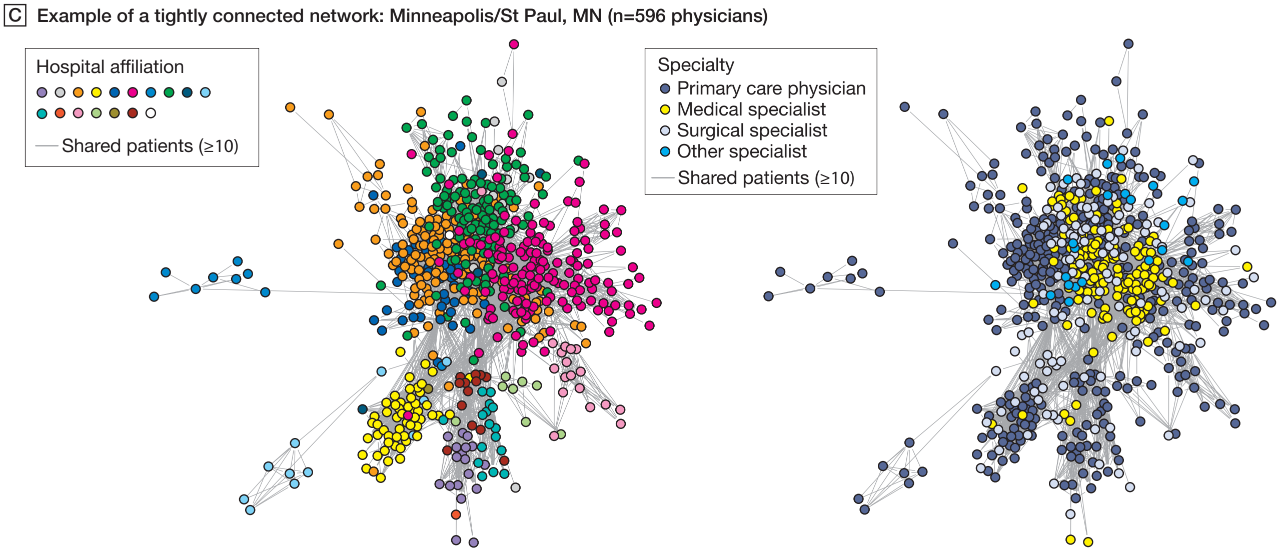
In networks with more physician connections across hospitals, the hospital clusters are closer together and the overall network becomes tighter.

In a network with many physician connections both within and across hospitals, the hospital clusters are tightly connected to each other.

B Example of a loosely connected network: Albuquerque, NM (n=1391 physicians)



C Example of a tightly connected network: Minneapolis/St Paul, MN (n=596 physicians)



panel increases the likelihood of a connection between physicians. This extends prior research by incorporating measures of the strength of the tie and by examining predictors of ties.[19] Our work also extends prior research focused on restricted types of care (eg, intensive care) or physicians (eg, urologists).[20,21]

The network interactions among physicians that we discerned differ from the formal networks sometimes established by health plans or health systems because they reflect actual patient flows across physicians. Formal networks are important, as evidenced by the unsurprising finding that physicians associated with the same hospital are far more likely than other physicians to be connected. Yet this is not always the case. For instance, although hospital affiliation appears to be a strong predictor of ties in the Albuquerque, New Mexico, market, this is not the case in Minneapolis/St Paul, Minnesota.

Our ability to discern these organic, natural networks is relevant to the current push toward the creation of accountable care organizations. Herein, we defined and identified natural groupings of physicians who were already sharing patients to provide care. Such physicians had a history of working with each other, and likely have evolved natural communication channels. Insurers and policy makers who want to influence physician behavior might therefore find it more efficient to identify candidate accountable care organizations in this fashion.

When asked, physicians almost uniformly report that they choose other physicians for advice or referrals because of their skill and clinical expertise.[22-24] Physician associations are more complex and are related to other factors as well. Physicians demonstrate homophily in their professional networks just as in virtually every other social circumstance studied.[25-27] Because our data are cross-sectional, we cannot tell whether physicians preferentially choose to refer to physicians who treat similar patients or whether these physicians share similar patient populations for other reasons. It is notable, however, that these findings hold even when accounting for hospital affiliation. The extent of homophily we observe has additional implications: it might reduce the diffusion of valuable or novel information, and it could also increase the consistency of clinical practice. That is, to the extent that when physicians are connected to other physicians that they resemble, they are less likely to be exposed to novel information.

These analyses are subject to several limitations. First, we used Medicare data to identify shared patients among physicians. Patient-sharing patterns may differ for younger patients or patients in integrated delivery systems. The growing availability of all-payer databases at the state level should facilitate more complete ascertainment of physician networks, although the Medicare data continue to have the advantage that they are available across the entire country. Second, our data were limited to a single year. Future analyses should replicate our findings using multiple years of data and examine the stability of networks over time. Third, our analyses of network char-

Table 2. Physician and Patient Characteristics Associated With Physician-Physician Relationships

Characteristics	Unadjusted Proportion of Dyads, Mean Difference: With Ties	Without Ties	Rate Ratio (95% CI)[a]: Unadjusted	Adjusted[b]
Physicians				
Overall difference	92.2	7.8		
Sex				
Male-male	65.1	54.6	1.68 (1.68-1.69)	1.32 (1.32-1.32)
Female-female	3.8	6.5	0.72 (0.71-0.72)	0.79 (0.78-0.79)
Male-female	29.1	36.8	1 [Reference]	1 [Reference]
Difference in age	11.5	12.5	0.80 (0.80-0.80)	0.88 (0.88-0.88)
Specialty				
PCP-PCP	10.1	15.8	0.77 (0.76-0.77)	0.62 (0.62-0.62)
PCP-medical	28.0	27.1	1 [Reference]	1 [Reference]
PCP-surgical	17.5	20.3	0.72 (0.72-0.72)	0.65 (0.65-0.65)
Medical-medical	16.9	12.1	1.52 (1.52-1.53)	1.36 (1.36-1.36)
Medical-surgical	20.7	17.9	0.94 (0.94-0.95)	0.90 (0.89-0.90)
Surgical-surgical	7.0	6.7	0.76 (0.76-0.77)	0.66 (0.66-0.66)
Office distance, km	21.1	38.7	0.99 (0.99-0.99)	0.98 (0.98-0.98)
Different hospital, %	69.2	96.0	0.07 (0.07-0.07)	0.12 (0.12-0.12)
Completed medical school at different medical school	6.1	3.6	0.53 (0.53-0.53)	0.99 (0.99-0.99)
Completed residency at different institution	5.3	2.7	0.55 (0.54-0.55)	0.88 (0.88-0.89)
Practice style[c]	0.29	0.31	0.91 (0.91-0.91)	0.93 (0.92-0.93)
Patients				
Difference in %				
Whites	11.5	20.2	0.72 (0.72-0.72)	0.89 (0.89-0.89)
Blacks	8.8	14.0	0.75 (0.75-0.75)	0.92 (0.92-0.92)
Hispanics	2.9	5.3	0.59 (0.59-0.59)	0.75 (0.75-0.76)
Females	13.0	15.6	0.80 (0.80-0.81)	0.86 (0.86-0.86)
Medicaid	15.3	24.4	0.69 (0.69-0.69)	0.86 (0.86-0.86)
Difference in age	4.1	5.4	0.42 (0.42-0.42)	0.75 (0.75-0.75)
Hierarchical clinical conditions score	1.0	1.1	0.78 (0.78-0.78)	0.93 (0.93-0.93)

Abbreviation: PCP, primary care physician.
[a] Rate ratios reflect the increase in the expected number of shared patients (and thus likelihood of a true information sharing relationship) for every 10% point difference in patient panel characteristics (not applicable to hierarchical clinical condition score). All comparisons yielded *P* values of less than .001.
[b] Calculated using a negative binomial regression model adjusted for all variables in the table. Rate ratios were used because the outcome (number of shared patients) is a count rather than binary. Results were similar when a binary outcome variable was analyzed using logistic regression.
[c] Measured by episode treatment group intensity score.

acteristics included physician ties only if they were in the top 20% of ties for each individual physician. Some ties that we eliminated were likely to be true information-sharing relationships and conversely some that we retained may be ad hoc or happenstance (though our sensitivity analyses confirmed the robustness of the findings). Moreover, our approach fails to capture physician interactions with other physicians across the country through professional societies and likely underestimates information sharing among physicians within a specialty. Fourth, our model of characteristics associated with ties assumes conditional independence of dyads; currently available statistical methods precluded accounting for potential network-generated dependencies in data sets of our size. Fifth, the rapid adoption of electronic medical records since 2006 could lead to different relationship patterns.[28] Sixth, although we demonstrate variation in networks across geographic areas, additional research is needed to establish whether network characteristics are associated with variations in care.

In conclusion, we used novel methods to define social networks among physicians in geographic areas based on shared patients, examined how such networks vary across different geographic regions, and identified physician and patient population factors that are associated with physician patient-sharing relationships. This approach might have useful applications for policy makers seeking to influence physician behavior (whether related to accountable care organizations or innovation adoptions) because it is likely that physicians are strongly influenced by their network of relationships with other physicians.

Author Contributions: Dr Landon had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.
Study concept and design: Landon, Keating, Barnett, Onnela, O'Malley, Christakis.
Acquisition of data: Landon, Christakis.
Analysis and interpretation of data: Landon, Keating, Barnett, Onnela, Paul, O'Malley, Keegan, Christakis.
Drafting of the manuscript: Landon, Onnela, O'Malley, Christakis.
Critical revision of the manuscript for important intellectual content: Keating, Barnett, Paul, O'Malley, Keegan, Christakis.
Statistical analysis: Landon, Barnett, Onnela, Paul, O'Malley.
Obtained funding: Landon, O'Malley, Keegan, Christakis.
Administrative, technical, or material support: Keegan, Christakis.
Study supervision: O'Malley, Christakis.

Conflict of Interest Disclosures: The authors have completed and submitted the ICMJE Form for Disclosure of Potential Conflicts of Interest. Drs Landon and Christakis have an equity stake in a company, Activate Networks, which is licensed by Harvard University to apply some of the ideas embodied in this article. Dr Landon reported serving on the scientific advisory board for Activate Networks; serving on the medical advisory board for Navigenics; and serving as a consultant to the Massachusetts Medical Society, United Biosource, and Research Triangle Institute. Dr Barnett reported serving as a consultant to Ginger.io and having a patent application pending. Dr Onnella reported serving as consultant to MedNetworks. Dr O'Malley reported serving as a consultant to Daller Shaller Consulting and receiving reimbursement for travel expenses from the National Institutes of Health. Dr Christakis reported serving on the scientific advisory board for and as a consultant to Activate Networks. No other authors reported disclosures.

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Online-Only Material: The eAppendix, eTable, eFigures 1 through 3, and interactive that goes with Figure 2A are available at http://www.jama.com.

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