Behavioral Health's Integration Within a Care Network and Health Care Utilization

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Objective. Examine how behavioral health (BH) integration affects health care costs, emergency department (ED) visits, and inpatient admissions.

Data Sources/Study Setting. Truven Health MarketScan Research Databases.

Study Design. Social network analysis identified “care communities” (providers sharing a high number of patients) and measured BH integration in terms of how connected, or central, BH providers were to other providers in their community. Multivariable generalized linear models adjusting for age, sex, number of prescriptions, and Charlson comorbidity score were used to estimate the relationship between the centrality of BH providers and health care utilization of BH patients.

Data Collection/Extraction Methods. Used outpatient, inpatient, and pharmacy claims data from six Medicaid plans from 2011 to 2013 to identify study outcomes, comorbidities, providers, and health care encounters.

Principal Findings. Behavioral health centrality ranged from 0 (no BH providers) to 0.49. Relative to communities at the median BH centrality (0.06), in 2012, BH patients in communities at the 75th percentile of BH centrality (0.31) had 0.2 fewer admissions, 2.1 fewer all-cause ED visits, and accrued \$1,947 fewer costs, on average.

Conclusions. Increased behavioral centrality was significantly associated with a reduced number of ED visits, less frequent inpatient admissions, and lower overall health care costs.

Key Words. Social network analysis, integrated behavioral network, health care costs, emergency and hospital utilization, substance use disorder, mental health

The relationship between variation in health care and patient-level costs and outcomes has been actively investigated for decades. Integration and collaboration among providers of different specialties are considered an important area of research in the health care field, especially in the context of recent

health care reform (Freeman 1978; Cunningham et al. 2011; Casalino et al. 2015). In particular, the integration of behavioral health services (i.e., substance abuse and mental health treatment) with general medical care has become a policy priority in recent years (Alakeson and Frank 2010; Beronio, Glied, and Frank 2014; Stewart et al. 2017). However, the extent to which behavioral health is integrated into the health care system and the effects of the amount of behavioral health integration on patient outcomes have not been widely studied (Bramesfeld et al. 2011).

Within patient-sharing networks, physicians are considered connected to each other if they provide care to the same patient either during a particular episode or over time. Greater integration of behavioral health providers into a care network may indicate a greater level of meaningful communication and collaboration among patients' health care professionals. Such integration is recognized as a catalyst for improved patient outcomes, such as reduced hospital length of stay (Baggs et al. 1999; Casalino et al. 2015; Moen et al. 2016), decreased mortality (Knaus 1986; Cunningham et al. 2011), and higher patient satisfaction (Freeman 1978; Katon and Unützer 2013). Analysis of formal and informal physician partnerships, identified in terms of the patients they share, may be an approach that helps describe differences in health care quality, outcomes, and costs. This approach may be particularly useful in the areas of mental health and substance use disorders (Substance Abuse and Mental Health Services Administration 2016). These are often chronic conditions that affect all aspects of patient health and patient interaction with the health care system.

The importance of incorporating behavioral health into all aspects of health care is well established (Uddin, Hossain, and Kelaher 2011; Uddin et al. 2013; Linardakis et al. 2015; Tintorer et al. 2015). Care coordination across multiple care settings is recognized as an important aspect of quality behavioral health care (Guerrero et al. 2016). To provide the highest quality care possible, patients with behavioral health conditions need to receive integrated care coordination rather than piecemeal care (Johnston, Peppard, and

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Newton 2015). These patients are often medically complex in ways that differ from patients with other types of conditions (Roberts et al. 2015). Their care needs frequently oscillate between severe or urgent and more chronic or ongoing. Further, their behavioral health treatment both directly and indirectly affects other aspects of their health care.

This study applied social network analysis (SNA) to 3 years of Medicaid data from six states to identify patterns of provider patient sharing, or *care communities*. We then analyzed the structure of these communities to estimate how greater behavioral health integration was related to total health care cost, emergency department (ED) visits, and inpatient admissions among individuals with a behavioral health disorder.

METHODS

We conducted a multivariable analysis of health care costs and utilization among patients identified as being treated for a mental health or substance use disorder. We examined the association between behavioral health integration and three utilization outcomes: total health care costs, number of ED visits, and number of inpatient admissions. Through SNA, we identified areas of strong provider integration and collaboration, which we termed *care communities*, and we assessed the integration, or centrality, of behavioral health providers within each.

The data were administrative billing records from six Medicaid insurance plans in the Truven Health MarketScan Multi-State Medicaid Database. The database contains person-level health care claims information from all settings of care. Individual patients can be tracked over time and across providers.

Our SNA identified care communities using data from all patients from 2011 through 2013. The utilization analysis, which was limited to patients with behavioral health conditions, also used data from 2010 through 2013. We chose this analysis period to avoid bias from any potential effects of the Affordable Care Act.

Social Network Analysis and Identification of Care Communities

Our application of SNA to the MarketScan Medicaid data had two steps. The first identified subnetworks of densely connected providers—the care communities. Following earlier studies (Pham 2009; Barnett et al. 2011, 2012; Pollack

et al. 2014), we defined two physicians as connected if they had an encounter with the same patient within the same calendar year. We then defined care communities as groups of physicians that were densely connected within the group but sparsely connected between groups. They were identified using the Clauset–Newman–Moore algorithm (Clauset, Newman, and Moore 2004). To prevent changes in enrollment from artificially affecting the composition of care communities, connections were equally weighted across the years 2011–2013.

The focus of the second step was determining the centrality of behavioral health providers for each year within each care community. Providers were placed into one of 11 groups according to their specialty: Behavioral Health, Ambulatory Surgery, Primary Care, Emergency Department/Urgent Care, Specialty Care, Complementary and Alternative Medicine, Hospital-Based Care, Inpatient Surgery, Geriatric Care, Other Facility-Based Care, and Other. Further analysis indicated that Geriatric Care specialties tended to serve as primary care providers for the older population, and these specialties were incorporated into Primary Care.¹

We determined the strength of the connection between two provider groups for a given year by summing the total number of shared patients (i.e., patients who saw a provider in each group). Using these aggregated connections, we calculated behavioral health provider group integration within a care community-year—the measure of interest for our multivariable analysis—as the behavioral health provider group’s eigenvector centrality (Bonacich 1987). Measures of behavioral health centrality were calculated only for communities with 10 or more providers in at least one of the three study years, and they were calculated only for those years where there were 10 or more active providers.

All network analyses were conducted using the *igraph* (Csardi and Nepusz 2006) package of the R statistical programming language. More complete details on our SNA can be found in the Appendix SA2.

Identification of Behavioral Health Patients and Analysis of Utilization Outcomes

The analytic sample comprised enrollees with a diagnosis of a mental health and/or substance use disorder who met the following criteria: an index event, defined as the first medical encounter for the patient in the calendar year; age over 18 on the day of the index event (the index date); a behavioral health diagnosis in the 12 months before the index date; and continuous enrollment in a single health plan for 12 months before and 12 months after the index

date. Thus, the 2011 analytic sample comprises patients with a behavior health diagnosis in 2010 who were continuously enrolled in the same plan in 2011. The sample was restricted to those who were continuously enrolled for 12 months after the index date to insure that a full course of treatment could be observed. Behavioral health conditions were identified using International Classification of Diseases, Ninth Revision (ICD-9) diagnosis codes, outpatient prescription use, or both. The appendix (Table S5) provides details on the diagnosis codes and prescriptions used and an example of this procedure.

Patients were attributed to the care community where they had the largest number of encounters. If a patient had the same number of encounters in two or more care communities, the patient was attributed to the care community where he or she had the greatest number of primary care encounters. The community's behavioral health centrality score for the year was assigned following patient attribution.

We examined three outcomes: (1) total paid amount, defined as the total amount reimbursed by the Medicaid plan (which excludes out-of-pocket costs); (2) number of ED visits; and (3) number of inpatient stays.

For ED visits and inpatient stays, we modeled the probability of any events and the count of events (including zero). We hypothesized that the total amount paid would be negatively related to the centrality of behavioral health within the care community providing the majority of a patient's care. Similarly, we hypothesized that the likelihood and number of ED visits and inpatient admissions would be negatively related to the centrality of behavioral health. We further suspected that the relationship with ED use would differ depending on the type of emergency care used. Thus, we looked at ED visits related to behavioral health as a separate outcome.

All models adjusted for patient demographics (age group and sex), medical complexity, and financial burden. Medical complexity was measured by the Charlson comorbidity score (Deyo 1992) and the number of different outpatient pharmaceuticals with a fill during the 12 months prior to the index date. Charlson comorbidity scores were categorized as low (score of 0–1), medium (2), or high (3 or more). Prescription drug use was categorized as zero, one, two, or three or more prescriptions.

Multivariable Models

For the continuous, heavily skewed outcome of medical utilization, we fit a log-linear model with gamma-distributed errors. The counts of ED visits and

inpatient encounters exhibited a considerable number of zero values, so zero-inflated Poisson models were specified on the basis of tests of over-dispersion. This approach separately estimates the likelihood of an encounter and the number of encounters. All models controlled for analysis year and Medicaid plan.

RESULTS

We first present brief results from the SNA and estimation of behavioral health centrality. This is followed by findings from the analysis of our primary outcomes of interest: total utilization, ED visits, and inpatient admissions.

Community Structure and Behavioral Health Centrality

Table 1 summarizes the results of the SNA that identified the subnetworks (care communities) within each of the six Medicaid plans as well as the centrality of behavioral health providers within the identified care communities from 2011 through 2013.

The upper portion of Table 1 summarizes how the size and growth of the Medicaid plans varied over the 3 years. On average, plan enrollment increased 6 percent from 2011 to 2013, with a range of <1 to 13 percent. The number of providers considered for the network analysis similarly varied across plans and time, growing an average of 36 percent over 2 years.

Additional analysis (not reported) indicates that the number of providers in the two Medicaid plans with stable enrollment numbers decreased from 2011 to 2013 by 5.9 and 11.4 percent, respectively. The increase in providers among the remaining four plans was 171, 37.7, 18.1, and 6.6 percent, respectively. Most of the growth in the number of providers for the outlying plan with a 171 percent increase occurred between 2012 and 2013, when the number of providers increased by 154 percent. An example of a care community from this plan is explored in the lower portion of Figure 2.

Identified Care Communities. The second section of Table 1 describes the general network structure and number of identified care communities across years. Unlike enrollment and the number of providers, the average number of shared patients (connections between included providers) across plans did not show a consistent trend over time. Compared with 2011, there were fewer

Table 1: Summary of Network Analysis

Measure	Study Year		
	2011	2012	2013
Summary of included Medicaid plans			
Number of enrollees (N)			
Average	1,061,626	1,112,490	1,130,292
Largest	2,153,699	2,318,235	2,365,198
Smallest	299,189	301,178	300,655
Number of providers considered for care communities [†]			
Average	22,077	23,357	28,632
Largest	62,211	66,346	73,857
Smallest	2,718	2,604	2,556
Summary of overall network structure			
No. of edges (sharing of patients) [‡]			
Average	19,337,038	17,880,936	18,919,901
Largest	46,798,888	41,796,159	49,822,130
Smallest	1,753,756	1,724,584	1,902,254
Summary of larger care communities [¶]			
No. of care communities	42	46	46
Total no. of providers	132,360	138,658	158,042
Largest care community (no. of providers)	23,252	25,081	27,951
Smallest care community (no. of providers)	26	24	110
Average no. of providers within care communities	3,096	2,998	3,685
No. of edges (shared patients) [‡]			
Average	3,014,148	2,510,942	2,342,466
Median	474,735	463,828	539,636
Summary of behavioral health presence within larger care communities			
No. of edges (shared BH patients) [§]			
Average	189,640	178,943	124,865
Median	97,638	96,663	50,055
Centrality of BH providers ^{**}			
Average	0.16	0.15	0.17
Max	0.45	0.46	0.49
Min	0.00	0.00	0.01

[†]Number of provider IDs after removing all excluded categories (see Figure S1).

[‡]The total number of “connections” between any two providers in row two. This is defined as a patient seeing both providers within the same payer year. Thus, an individual may account for multiple edges.

[¶]Defined as an identified edge from prior row where one of the two providers was classified as a behavioral health provider (see Appendix SA2 for classifications).

[§]Minimum size of 10 providers and active within the year.

^{**}Computed as eigenvector centrality where: 0 = completely disconnected from all other provider types and 1 = connected to all other provider types in the community.

BH, behavioral health.

connections in 2012 for five of six plans and more connections in 2013 for four of six plans.

An active community within a year is one where patients had multiple care encounters with that community's providers. Because enrollment size and the number of providers changed over time, not all identified care communities were "active" (i.e., shared patients between providers) during all 3 years. In results not shown in the table, we identified a total of 112 care communities. Of these, 64 were active in 2011, 61 in 2012, and 109 in 2013. This echoes the count of shared patients, which was lowest in 2012 and highest in 2013. This activity was driven by a single Medicaid plan that exhibited large increases in numbers of enrollees and providers from 2012 to 2013 (154 and 116 percent, respectively).

Behavioral Health Centrality within Care Communities. The third and fourth sections of Table 1 summarize the larger care communities. We identified 47 communities across the 3 years. There were 42 communities with 10 or more active providers in 2011, increasing to 46 communities in 2012 and 2013. Community size ranged from 24 to 27,951 active providers, with an average size of approximately 3,000. All of these included at least one behavioral health provider, although in some years, no behavioral health provider was active in the community (resulting in a behavioral health centrality score of zero). The centrality of behavioral health remained stable across the study period at approximately 0.16, with a maximum centrality of 0.49.

The structure and role of behavioral health varied considerably between these communities. Figure 1 maps four communities in 2013. Each is from a different Medicaid plan, and a node's proximity to the origin represents its centrality. Primary care had the greatest centrality within three of the communities (A, C, and D), and hospital care had the greatest centrality in community B. Although hospital and primary care were the center of communities B and C, respectively, communities A and D did not fully center on a specific type of care. Instead, several types of care shared similar levels of centrality.

The role of behavioral health also varied over time within care communities. Figure 2 illustrates how care communities changed over time. The upper portion of the figure shows community D (from Figure 1). This community, whose centrality was balanced across multiple types of care, showed a relatively stable structure over time. In contrast, community A (from Figure 1) displayed larger changes because the plan had substantial growth in enrollment and providers. This community was inactive in 2011, and its size increased dramatically by 2012.

Figure 1: Variation in Community Structure and Behavioral Health Centrality: Select Communities—2013

pc = Primary Care; spec = Outpatient Specialty Care; bh (Black Node) = Behavioral Health; amb_surg = Ambulatory (Outpatient) Surgery; hosp = Hospital-Based Care; ed_uc = Emergency Department/Urgent Care; in_surg = Inpatient Surgery; cam = Complementary and Alternative Care; other_fac = Other Facility-Based Care; other = all Other Providers (Technicians, Physical Therapy, Health Educator, etc.). (See Table S3 for full listing.)

Notes. The 2013 mappings of four communities from four different payers are plotted. The size of each vertex (node) reflects its relative number of patient encounters (i.e., weight); the size of each connection (edge) reflects the number of shared patients between the two provider types (i.e., strength of connection). These are scaled for each graph and do not reflect the underlying size of the community. “Self-edges,” or loops, reflect shared patients between providers of the same group. The greater a node’s centrality, the closer it is to the origin. However, coordinate signs are arbitrary, and a node’s quadrant has no interpretation.

Utilization Analysis

Descriptive Statistics. Table 2 summarizes descriptive statistics of the population with a behavioral health condition. We identified 234,886 patients in 2011. This increased to 251,666 in 2012 before decreasing to 242,909 in 2013. Approximately 22 percent (21.5, 22.4, and 21.6 percent by year) of the patients with behavioral health conditions had at least one inpatient admission, with

Figure 2: Communities and Behavioral Health Centrality over Time

pc = Primary Care; spec = Outpatient Specialty Care; bh (Black Node) = Behavioral Health; amb_surg = Ambulatory (Outpatient) Surgery; hosp = Hospital-Based Care; ed_uc = Emergency Department/Urgent Care; in_surg = Inpatient Surgery; cam = Complementary and Alternative Care; other_fac = Other Facility-Based Care; other = all Other Providers (Technicians, Physical Therapy, Health Educator, etc.). (See Table S3 for full listing.)

Notes. Two of the care communities from Figure 2 are plotted over the three study years. All communities were identified using combined data from 2011 to 2013. Then, the structure and centrality within each community were plotted using each year's data separately. The size of each vertex (node) reflects its relative number of patient encounters (i.e., weight); the size of each connection (edge) reflects the number of shared patients between the two provider types (i.e., strength of connection). "Self-edges," or loops, reflect shared patients between providers of the same group. X and Y axes are shown as gray, dashed lines. The greater a node's centrality, the closer it is to the origin. However, coordinate signs are arbitrary, and a node's quadrant has no interpretation.

approximately 7.5 percent (7.4, 7.9, and 7.4 percent) having two or more inpatient admissions.

The entire sample had a high frequency of ED encounters. Nearly half (45.1, 50.1, and 48.4 percent) had at least one ED visit, and nearly 20 percent (17.1, 19.1, and 18.3 percent) had multiple ED visits. Similarly, nearly one-fifth had an ED visit pertaining to mental health (19.6, 21.5, and 20.5 percent) or a substance use disorder (16.9, 19.3, and 18.9 percent).

A small number of individuals identified as having a behavioral health condition incurred no medical costs during the analytic year (0.7 percent in 2011, 1 percent in 2012, and 0.7 percent in 2013). Among those who did incur costs, the pattern was typical of health care costs data. The average amount was \$13,291 (standard deviation [SD] \$23,851) in 2011, \$14,726 (SD \$23,416)

Table 2: Summary of Health Care Utilization by Patients with Behavioral Health Conditions

<i>Measure</i>	<i>2011</i>		<i>2012</i>		<i>2013</i>	
	<i>No.</i>	<i>% (SD)</i>	<i>No.</i>	<i>% (SD)</i>	<i>No.</i>	<i>% (SD)</i>
Total, <i>N</i> [†]	234,886	100.0	251,666	100.0	242,909	100.0
Outcome variables						
Inpatient admissions						
At least 1 admission	50,579	21.53	56,304	22.37	52,397	21.57
2–3 admissions	13,799	5.87	15,382	6.11	14,099	5.80
4 or more admissions	3,703	1.58	4,535	1.80	3,950	1.63
ED utilization						
1 service related to the ED	65,905	28.06	78,182	31.07	73,151	30.11
2–3 services	11,921	5.1	14,863	5.9	14,024	5.8
4 or more services	28,196	12.0	33,092	13.1	30,357	12.5
MH ED visits	46,069	19.6	54,146	21.5	49,871	20.5
SUD ED visits	39,727	16.9	48,686	19.3	45,815	18.9
Amount paid, \$						
Total with utilization [‡]	233,201	99.3	249,190	99.0	241,272	99.3
Average amount paid among those with utilization	13,291	23,851	14,726	25,416	14,370	25,844
Primary predictors of interest						
Centrality of behavioral health providers [§]						
Average	0.14	0.15	0.15	0.16	0.14	0.19
Max	0.98		0.98		0.99	
Min	0.00		0.00		0.10	
Covariates						
Sex						
Female	143,082	60.9	152,526	60.6	146,904	60.5
Male	91,804	39.1	99,140	39.4	96,005	39.5
Age						
18–39	84,961	36.2	92,167	36.6	85,776	35.3
40–64	124,881	53.2	132,470	52.6	128,709	53.0
65+	25,044	10.7	27,029	10.7	28,424	11.7
Prescription drug claims						
None	52,856	22.5	58,984	23.4	77,700	32.0
One	8,288	3.5	8,841	3.5	7,638	3.1

continued

Table 2. Continued

Measure	2011		2012		2013	
	No.	% (SD)	No.	% (SD)	No.	% (SD)
Two	7,144	3.0	7,287	2.9	6,241	2.6
Three or more	166,598	70.9	176,554	70.2	151,330	62.3
Charlson comorbidity score						
No risk (0)	110,401	47.0	118,482	47.1	111,384	45.9
Low (1)	60,595	25.8	64,415	25.6	61,303	25.2
Medium (2)	26,721	11.4	28,267	11.2	27,984	11.5
High (3 +)	37,169	15.8	40,502	16.1	42,238	17.4

[†]A count of insured individuals in that year (i.e., person-years) attributed to a care community with 10 or more providers. If a person remains insured for multiple years, that person will be counted as a separate person-year for each year he/she is insured and identified. For instance, a person with a BH diagnosis that is insured all 3 years will be counted in 2011, 2012, and 2013. A person with a BH diagnosis insured in 2011 and 2013, but not 2012, will only be included in 2011 and 2013.

[‡]To reduce issues of confounding, the prior year's data were used to identify the sample and comorbidities. Thus, the sample is limited to individuals with at least 24 months of continuous enrollment. For example, those with a BH diagnosis in 2010 who were also enrolled in 2011 comprise the 2011 sample, and a small portion remained enrolled but had no utilization in 2011.

[§]A total of 4,880 person-years were attributed to communities with no behavioral health providers for that year (Figure 2, Community A illustrates how BH integration may change within a community over time). The behavioral health patients may include those being treated for depression by an SSRI managed by a primary care provider, an emergency department visit for a drug overdose, or an inpatient admission for a severe mental health or substance use episode where a behavioral health provider was not involved.

BH, behavioral health; ED, emergency department; MH, mental health; SUD, substance use disorder.

in 2012, and \$14,370 (SD \$25,844) in 2013. Those averages exceeded median values (\$3,576, \$4,486, and \$4,062) and were driven by a small number of high-cost cases. The maximum cost each year was \$999,558 in 2011, \$1,066,077 in 2012, and \$1,042,741 in 2013.

Just over 60 percent of patients (60.9, 60.6, and 60.5 percent) were female, and nearly 90 percent were aged 18 to 64 (89.3, 89.3, and 88.3 percent). Nearly 50 percent (47, 47.1, and 45.9 percent) had a Charlson comorbidity score of zero, and an additional quarter (25.8, 25.6, and 25.2 percent) had a score of 1. Consistent with having an identified behavioral health condition, most (77.5, 76.2, and 68.2 percent) had at least one active prescription; a majority of the sample each year (70.9, 70.2, and 62.3 percent) filled three or more prescriptions for any type of medication.

Multivariable Models. Table 3 summarizes results of the four multivariable models that examined the relationship between the outcomes of interest and

the behavioral health centrality within the care community providing the majority of each patient's care.

The results in Table 3 are organized in the following manner. For each modeled outcome, the table presents the marginal effect and the predicted value of the outcome at the 25th, 50th (median), and 75th percentiles of the behavioral health centrality, while holding all other covariates at their sample mean. For the continuous cost outcome, these represent the marginal effects and predicted amounts paid. For all other outcomes (inpatient admissions, ED visits, and behavioral health ED visits), the likelihood of any utilization and the number of expected encounters are provided.

After adjustment for age, sex, Charlson comorbidity score, and the number of prescription medications, there was a significant and negative relationship between the centrality of health care providers and total reimbursed medical costs (i.e., amount paid) for the population with a behavioral health condition ($p < .001$). In other words, the more centralized behavioral health was within an identified community of care, the lower the expected cost of health care utilization among patients with behavioral health conditions.

Panel I of Table 3 illustrates this relationship. In 2011, the predicted costs for a patient receiving care in a community with a relatively low behavioral health centrality (e.g., 25 percent of communities had a BH centrality of 0.01 or lower) were \$15,335 (95 percent confidence interval [95% CI], \$15,102, \$15,572). If that patient was part of a community with a median level of behavioral health centrality (0.06), their expected costs would decrease \$432 from \$15,335 to \$14,903 (95% CI, \$14,692, \$15,117). If their community's behavioral health centrality was at the 75th percentile (0.31), their expected costs would drop an additional \$1,696 to \$13,207 (95% CI, \$12,973, \$13,445).

Consistent with the relationship between behavioral health centrality and total health care utilization, the likelihood of any inpatient admission and the total number of expected admissions decreased as the centrality of behavioral health increased within a care community. As illustrated in the Marginal Impact column of the first section of Table 3 Panel II, at the 25th percentile of behavioral health centrality, an incremental increase in behavioral health centrality of 0.01 decreased the likelihood of any inpatient admissions by 0.12 percent (95% CI, -0.18% , -0.1%).

The second section of Panel II in Table 3 reports the expected number of inpatient admissions. The marginal effects column indicates that at the median value of behavioral health centrality, the marginal impact of increasing the centrality of behavioral health providers by 0.01 would be an estimated

Table 3: Marginal Impacts of Behavioral Health Centrality and Predicted Outcomes

<i>Study Outcome</i>	<i>Behavioral Health Centrality[†]</i>	<i>Marginal Impact[‡]</i> (95% CI)	<i>2011 Predicted Mean[§]</i> (95% CI)	<i>2012 Predicted Mean[§]</i> (95% CI)	<i>2013 Predicted Mean[§]</i> (95% CI)
I. Amount paid, \$					
	25th percentile	-7.85 (-8.65, -7.02)	15,335 (15,102, 15,571)	17,612 (17,320, 17,908)	17,333 (17,017, 17,654)
	0.01				
	Median	-7.65 (-8.44, -6.84)	14,903 (14,692, 15,117)	17,115 (16,850, 17,385)	16,845 (16,555, 17,139)
	0.06				
	75th percentile	-6.86 (-7.55, -6.16)	13,207 (12,973, 13,445)	15,168 (14,887, 15,454)	14,928 (14,635, 15,226)
	0.31				
II. Inpatient admission: Likelihood of admission [¶] (Extensive margin)					
	25th percentile	-0.12 (-0.18, -0.10)	25.6 (24.9, 26.4)	26.7 (25.9, 27.5)	26.6 (25.7, 27.6)
	0.01				
	Median	-0.12 (-0.18, -0.10)	25.4 (24.8, 26.1)	26.5 (25.8, 27.3)	26.5 (25.6, 27.3)
	0.06				
	75th percentile	-0.11 (-0.18, -0.10)	24.7 (23.9, 25.6)	25.8 (24.9, 26.7)	25.7 (24.8, 26.7)
	0.31				
Number of admissions ^{**} (Intensive margin)					
	25th percentile	-0.05 (-0.04, -0.03)	1.2 (1.19, 1.25)	1.2 (1.20, 1.27)	1.2 (1.15, 1.23)
	0.01				
	Median	-0.04 (-0.05, -0.03)	1.2 (1.14, 1.19)	1.2 (1.16, 1.21)	1.1 (1.11, 1.17)
	0.06				
	75th percentile	-0.04 (-0.05, -0.02)	1.0 (0.94, 1.00)	1.0 (0.96, 1.02)	0.9 (0.92, 0.98)
	0.31				
III. ED use: Likelihood of use [¶] (Extensive margin)					
	25th percentile	0.38 (-0.44, 0.26)	62.2 (61.7, 62.8)	66.5 (66.0, 67.1)	67.0 (66.4, 67.6)
	0.01				
	Median	0.38 (-0.44, 0.26)	62.3 (61.8, 62.8)	66.6 (66.1, 67.1)	67.1 (66.5, 67.6)
	0.06				
	75th percentile	0.42 (-0.47, 0.28)	62.7 (62.1, 63.3)	66.9 (66.4, 67.5)	67.4 (66.8, 68.0)
	0.31				

continued

Table 3. Continued

Study Outcome	Behavioral Health Centrality [†]	Marginal Impact [‡] (95% CI)	2011 Predicted Mean [§] (95% CI)	2012 Predicted Mean [§] (95% CI)	2013 Predicted Mean [§] (95% CI)
Number of visits** (Intensive margin)	25th percentile	-0.14 (-0.10, -0.09)	14.0 (14.00, 14.09)	14.7 (14.63, 14.73)	15.0 (14.97, 15.08)
	0.01		13.5	14.1	14.4
	Median	-0.13 (-0.10, -0.09)	(13.46, 13.54)	(14.07, 14.16)	(14.39, 14.50)
	0.06		11.4	12.0	12.2
	75th percentile	-0.13 (-0.09, -0.08)	(11.39, 11.48)	(11.91, 12.00)	(12.19, 12.29)
IV. ED use for behavioral health: Likelihood of use [¶] (Extensive margin)	0.31		40.0	45.4	46.5
	25th percentile	0.21 (0.16, 0.28)	(39.4, 40.5)	(44.8, 46.1)	(45.8, 47.2)
	0.01		40.5	46.0	47.1
	Median	0.17, 0.29	(40.0, 41.0)	(45.4, 46.5)	(46.4, 47.7)
	0.06		42.7	48.2	49.4
Number of visits** (Intensive margin)	75th percentile	0.27 (0.20, 0.34)	(42.0, 43.4)	(47.5, 48.9)	(48.6, 50.1)
	0.31		12.6	12.6	12.7
	25th percentile	-0.08 (-0.06, -0.05)	(12.50, 12.63)	(12.49, 12.62)	(12.59, 12.74)
	0.01		11.9	11.8	12.0
	Median	-0.07 (-0.06, -0.05)	(11.81, 11.91)	(11.79, 11.91)	(11.89, 12.02)
	0.06		9.3	9.3	9.4
	75th percentile	-0.07 (-0.05, -0.05)	(9.23, 9.34)	(9.23, 9.34)	(9.30, 9.42)
	0.31				

[†]BH centrality quartiles correspond to values determined at the patient level (Table 2) and not across identified care communities (Table 1).
[‡]For the amount paid, this is the change in the amount paid because of a .01 increase in BH centrality. For the likelihood of inpatient admission and ED use, this is the change in the risk (probability) of any encounters because of a .01 increase in BH centrality. For the number of inpatient admissions and ED visits, this is the change in the expected number of visits because of a .01 increase in BH centrality.
[§]Predicted values are calculated holding all other covariates included in the final multivariable models fixed at annual sample average. For amount paid, this is the predicted amount at differing levels of BH centrality. For the likelihood of inpatient admission and ED use, this is the probability of having one or more visits during the year. For the number of inpatient admissions and ED visits, it is the expected number of encounters during the year.
[¶]Defined as 1 or more visits during the year.
^{**}Among those with at least one encounter during the year.
 BH, behavioral health; CI, confidence interval; ED, emergency department.

decrease of 0.04 inpatient admission per enrollee per year (95% CI, -0.05 , -0.03).

These effects are more noteworthy than they might appear. Among the 234,886 behavioral health patients in 2011, for instance, the marginal impact of this 0.01 increase in behavioral health centrality would be approximately 2,375 fewer inpatient admissions. This reflects a 0.12 percent decrease in the likelihood of any admission and 0.04 fewer admissions per person.

The relationship between behavioral health centrality and ED utilization is less clear. Panel III of Table 3 indicates that, for total (all-cause) ED visits, behavioral health centrality was not significantly related to the likelihood of having a visit. In 2013, the likelihood of an ED visit was 67.1 percent (95% CI, 66.5%, 67.6%) given the median value of behavioral health centrality. This likelihood increased to 67.4 percent (95% CI, 66.8%, 68.0%) at the 75th percentile. However, as indicated by the confidence intervals of the marginal impacts of the extensive margin, which all encompass zero, the actual relationship between behavioral health centrality and ED use is indeterminate. This is further supported by carefully comparing the confidence intervals of the estimated probabilities with corresponding point estimates. Returning to 2013, the 95% confidence interval of the likelihood of ED utilization at the median value of behavioral health centrality encompasses the point estimates at both the 25th percentile (67.0 percent) and the 75th percentile (67.4 percent) of behavioral health centrality.

However, centrality had a negative and statistically significant relationship with the expected number of all-cause ED visits. The second section of Table 3 Panel III indicates that increasing behavioral health centrality from the 25th to the 75th percentile in 2012 would decrease the expected number of ED visits by 2.7 (from 14.7 to 12.0). This effect dominates the positive (and insignificant) relationship between centrality and the extensive margin for ED visits. Even with the increased likelihood of any ED visit by 0.4 percent (from 66.5 to 66.9 percent) in 2012, there is a net per-person decrease of 1.75 ED visits. Based on a 2012 sample of 251,666 persons, this would result in 439,786 fewer ED visits.

Unlike all-cause ED visits, behavioral health centrality had a positive and significant relation to ED visits for behavioral health on the extensive margin (Table 3, Panel IV). As the centrality of behavioral health increased, so did the likelihood of ED utilization for behavioral health. As with all-cause ED visits, greater centrality also reduced the number of ED visits related to behavioral health (Table 3, Panel IV) by similar magnitudes.

DISCUSSION

This study used a large, multistate database of Medicaid billing data to identify groups of collaborating providers (care communities) through SNA. To our knowledge, this is one of the first investigations to use SNA to better understand the role of provider types—specifically behavioral health providers—within a network of collaborating physicians using data from the United States (Fuller et al. 2007; Barnett et al. 2015; Lorant, Nazroo, and Nicaise 2017). The provider–patient relationship has been a more common focus of research in the area of care collaboration. Research on collaboration between physicians has focused on the discussion of medical errors, collegial control, and other recognized negative aspects of medical care (Murcott 1977; Baron 1992). There also are investigations on the culture of medicine and physicians’ socialization of medical students, interns, and residents into that culture (Atkinson 1992). In contrast with those studies, our focus was to better understand the relationship between the degree to which behavioral health providers are integrated within a community of collaborating providers and the effects on their patients. In doing so, we discovered that the more integrated behavioral health providers are in a care community, the less reliant patients with behavioral health conditions are on hospital-based care. Also, emergency department utilization for all-cause and behavioral health visits was lower (as measured by the intensive margin) as behavioral health centrality increased. Further examination of this dynamic, which could include exploring any corresponding shifts in payment shares from emergency and inpatient care to behavioral health care, remains open for future research.

As with any study employing retrospective observational data, the sample identification strategy and analytic approach influence how the findings should be interpreted. When constructing the provider networks, we did not place geographic limitations on where and how subnetworks could form. Although this revealed actual patterns of provider integration and collaboration, it prevented us from exploring differences attributable to sociodemographic characteristics and other potential social determinants of health. Similarly, we chose to employ a broad definition in terms of the time between provider visits, the sequence of those visits, and the underlying reasons for them. This resulted in inclusion of a greater number of providers, but it also prevented us from exploring the role of care coordination. Finally, by employing a community approach to identifying a subnetwork, we could include a

greater number of providers. Compared with an alternative approach, such as component analysis, this resulted in subnetworks (care communities) of considerable size.

Decisions regarding how our analytic sample was identified and the rules used for who was included in the final analytic dataset also merit mention. To reduce the risk of confounding factors, we required 2 years of continuous enrollment. The first year was used to identify the sample and control variables, and the second year to construct the outcomes of interest. A long period of continuous enrollment reduced the sample size and excluded groups who obtain Medicaid coverage due to a specific condition or episode, such as pregnancy, and our final sample consisted of a high number of people with disabilities and/or with low income.

Similarly, limiting the analytic sample to patients attributed to a provider community large enough to determine the centrality of behavioral health providers implies that our findings are limited only to that subset of behavioral health patients with a relatively consistent source of care. Unfortunately, many individuals who currently have mental health illness or substance use disorders do not have this type of care. Next, the rule we used to place patients in care communities may have assigned some patients to the wrong care community. However, these misassignments likely were rare because a substantial majority of patients fell wholly into a single care community. Regardless, as long as the assignment process is not systemically related to behavioral health centrality, then the resulting estimation error is random and the estimates remain unbiased although less precisely estimated.

Finally, the decision to limit our analysis to a set of Medicaid plans is noteworthy because of the potential impacts to both the provider networks and patient populations. As Table 2 indicates, our population tended to be younger and different from either commercially insured or Medicare insured populations. Further, the structure of Medicaid plans likely influences provider behavior and subsequent collaborations in ways that commercial and Medicare plans may not.

Because of these limitations and the potential for unobserved confounding variables, the observed effect of behavioral health centrality on utilization may not be fully attributable to centrality alone. Other factors, such as the availability of behavioral health providers, may play a role; however, it is unlikely that what we observed is due solely to such confounding effects. Instead, the data do suggest behavioral health centrality plays an important role in health care utilization.

Despite these limitations, this work provides three important contributions. First, our study extends the approach used by prior researchers in building networks of medical care providers. Next, in contrast with prior research, we identified care communities by applying a data-driven method of community analysis at the provider level across multiple health plans and time. Finally, we grouped providers to sharply focus on the role of behavioral health providers. In doing so, we found a diversity of subnetwork structures, or care communities (Figure 1), and we gained an understanding of how their structure changed over time (Figure 2).

The key findings of this study have important implications for current policy. In March 2016, the Centers for Medicare & Medicaid Services (CMS) finalized its mental health and substance use disorder parity rule intended to strengthen access to behavioral health services and providers (CMS 2016). Our study suggests that in order for that rule to achieve its intended goals of improving access and reducing reliance on emergency and hospital-based care, it must be coupled with an adequate supply of behavioral health providers that are fully integrated into the larger provider care community. Such integration likely will take time, and evaluations of parity's impact will need to account for this transition.

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NOTE

1. Table S4 shows which specialties were assigned to the provider specialty groupings.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the supporting information section at the end of the article.

Appendix SA1: Author Matrix.

Appendix SA2: Technical Appendix.

Figure S1. Flow of Network Analysis.

Table S1. Heavily Connected Health Care Providers by Type.

Table S2. Impact on "Strength" of Health Care Provider Connections.

Table S3. Summary of Network Analysis Sensitivity.

Table S4. Provider Specialties by Group.

Table S5. Behavioral Health and Mental Health Diagnostic Codes.