

Trends in the Use of Clinical Decision Support by Health System–Affiliated Ambulatory Clinics in the United States, 2014-2016

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ABSTRACT

Objectives: Clinical decision support (CDS) is important for delivering high-quality care. We examined the use of 7 functions of CDS and changes over time in US health system–affiliated ambulatory clinics.

Study Design: We analyzed longitudinal data for 19,209 ambulatory clinics that participated in 3 years (2014-2016) of the Healthcare Information and Management Systems Society Analytics survey to assess use of 7 CDS functions and the characteristics of clinics associated with use of CDS.

Methods: We used descriptive statistics and linear probability models to assess the association of clinic characteristics (practice type, health system type, practice size) and 2 outcomes: CDS use during the study period and CDS use beginning in 2015 or 2016.

Results: Use rates increased between 2014 and 2016 for all 7 CDS functions, with increases ranging from 4 percentage points (genetic testing) to 13 percentage points (diagnostic result alerts). In 2016, the rate of use was highest for basic medication screening (61%), clinical guidelines and protocols (54%), and preventive medicine (57%). Lower use rates were observed for diagnostic result alerts (42%), remote device alerts (19%), incorporation of community-based electronic health record data into rules engines (26%), and genomics profiling in orders (9%). More than half of health systems, which included many smaller health systems, reported that none of their affiliated clinics used any CDS function. Affiliation with a multihospital health system and clinic size, but not clinic type (eg, primary care), were associated with a greater likelihood of use for most CDS functions.

Conclusions: Despite federal investment to promote health information technology adoption, substantial gaps remain in the use of CDS among ambulatory clinics, particularly among smaller health systems.

The American Journal of Accountable Care. 2019;7(4):4-10

Following federal incentives from Meaningful Use (MU) legislation to encourage the adoption of health information technology (IT), physicians in the United States have adopted electronic health records (EHRs) in growing numbers.¹⁻³ A 2015 survey found that 77.9% of office-based physicians reported using a certified EHR.⁴ EHRs include a range of health IT functionalities that can be adopted separately. One of the most well-studied EHR functionalities is clinical decision support (CDS). A systematic review of peer-reviewed studies published between 2007 and 2013 found 142 studies of the impact of CDS on patient care, with the majority of studies reporting positive results on quality, safety, or efficiency outcomes.⁵ MU incentives (now called Promoting Interoperability) defined CDS as a health IT functionality “that builds upon the foundation of an EHR to provide persons involved in care processes with general and person-specific information, intelligently filtered and organized, at appropriate times, to enhance health and health care.” To earn stage 2 MU incentives, for example, eligible providers were required to adopt drug-drug and drug-allergy interaction checks, as well as 5 CDS interventions related to their scope of practice or patient population.⁶ As the complexity of medical practice continues to increase, CDS tools will provide important support to providers to achieve high performance and succeed under payment arrangements that hold them accountable for cost and quality.

CDS has many functions, such as alerts for potential adverse drug events, clinical guidelines for use by clinicians at the point of care,

and notifications to flag abnormal diagnostic results.^{7,8} Although hospital use of CDS has been extensively studied,⁹⁻¹¹ less is known about use of CDS in ambulatory settings. To understand use of CDS in ambulatory care, we examined the use of 7 CDS functions and change in use between 2014 and 2016 among health system–affiliated ambulatory clinics, which represent a larger and growing proportion of clinics in the United States.

METHODS

Data Source

We used longitudinal data for 19,209 ambulatory clinics that participated in 3 years (2014, 2015, and 2016) of the Healthcare Information and Management Systems Society (HIMSS) Analytics survey from the HIMSS Analytics LOGIC Market Intelligence Platform.¹² The survey covered health system–affiliated clinics (approximately 42,000) in 50 states, the District of Columbia, and Puerto Rico, providing information on more than 75% of US health system–associated ambulatory care clinics. HIMSS defined clinics for this survey as ambulatory clinics providing preventive, diagnostic, therapeutic, surgical, and/or rehabilitative outpatient care for which the duration of treatment was less than 24 hours. HIMSS defined a health system as an organization composed of at least 1 hospital and its associated nonacute facilities. *Associated* was defined as a governance relationship (ie, owned, leased, or managed by a health system).

Approach

We included only clinics that completed the survey every year between 2014 and 2016. We excluded clinics ($n = 980$; 4.85%) that reported use of a CDS functionality in one year followed by nonuse in the subsequent year; it is unlikely that clinics would discontinue using a CDS function, so we assumed that the response was likely due to an error. The panel included 19,209 clinics affiliated with 1704 health systems as of 2016.

Clinic and Health System Characteristics

We used the HIMSS survey descriptive data to classify ambulatory clinics according to size (based on number of physicians, dichotomized into ≤ 3 and ≥ 4), clinic type (primary vs specialty), and health system type (single hospital or multihospital).

Study Outcome

We examined use of EHR and 7 functions of CDS that were defined in the HIMSS survey: (1) basic medication screening (drug-drug, drug-allergy), (2) clinical guidelines or protocols, (3) preventive medicine (eg, immunizations, follow-up testing), (4) alerts based on external EHR data (data from the community-based EHR is incorporated into the EHR's rules engine and triggers alerts), (5) genomics profiling used in orders (incorporated into the EHR and

could result in a suggested order or order change), (6) diagnostics result alerts (trigger relevant clinical alerts and clinical guidance/recommended care), and (7) remote device alerts (alert clinician when clinically significant changes in data are detected).

Responses were coded as a binary yes/no to indicate use during a given survey year. We calculated a composite binary variable that indicated whether the clinic used 1 or more of the CDS functions. The HIMSS survey did not capture data on extent of use of health IT functionalities.

Analysis

Descriptive statistics are presented here for each CDS function between 2014 and 2016 by clinics and by affiliated health systems. To understand changes in CDS use by health systems for each CDS function, the percentage of health systems was calculated for which none of the system's clinics had reported using it, for which all the system's clinics reported using it, and for which some but not all the system's clinics reported using it during the study period. Also calculated was the number of health systems that reported not using any CDS in any affiliated clinic.

To examine the association between clinic characteristics—clinic type (primary care vs specialty care), health system type (single- vs multihospital), and clinic size (≤ 3 vs ≥ 4 providers)—and use of each CDS function at any point during the 3-year analysis period, we used a linear probability model, using 2014 as the reference year and dummy variables for 2015 and 2016. In addition, to determine whether the magnitude of those same associations changed over time, for each CDS function, a linear probability model was used on the pool of clinics that did not report using the CDS function in 2014, with the dependent variable defined as reported CDS use in 2015 or 2016. Standard errors were clustered at the health system level.

RESULTS

Table 1 displays the characteristics of clinics and health systems in the analytic sample. Health systems had a mean of approximately 12 clinics per health system and 7 physicians per clinic in 2016. The number of reporting health systems declined by 113 (7%) between 2014 and 2016, likely mainly due to mergers and acquisitions. Nearly all ambulatory clinics (96%) had adopted EHRs by 2016. The majority of clinics provided primary care (64% in 2016) and were associated with a multihospital system (72% in 2016).

For every function of CDS, ambulatory clinic use increased between 2014 and 2016, ranging from an increase of 4 percentage points in genetics profiling used in orders to an increase of 13 percentage points for diagnostic result alerts. The portion of ambulatory clinics using any form of CDS increased from 53% in 2014 to 62% in 2016. Use of CDS was greatest for basic medication screening (61% in 2016), clinical guidelines and protocols (54% in

Table 1. Descriptive Characteristics of Health System–Affiliated Ambulatory Clinics, 2014–2016

	2014	2015	2016
Clinics, n	19,209	19,209	19,209
Health systems, n	1704	1648	1591
Clinics per health system, mean (SD)	11.27 (27)	11.66 (28)	12.07 (29)
Primary care clinics, n (% of total clinics)	12,495 (65)	12,390 (65)	12,353 (64)
Physicians per clinic, mean (SD)	6.91 (31.6)	6.89 (31.3)	6.94 (31.3)
Clinics with EHRs, n (%)	17,001 (89)	18,029 (94)	18,477 (96)
Primary care clinics with EHRs, n (% of primary care clinics)	11,041 (88)	11,591 (94)	11,846 (96)
Clinics in multihospital systems with EHRs, n (% of multihospital-system clinics)	12,014 (90)	13,039 (95)	13,508 (97)

EHR indicates electronic health record.

2016), and preventive medicine (57% in 2016), and CDS use was least for genomics profiling used in orders (9% in 2016) (**Figure 1**).

When assessed at the health system level, the majority of health systems reported that none of their ambulatory clinics were using CDS. This percentage decreased from 61% of health systems reporting no CDS use in 2014 to 55% in 2016. Of the 7 CDS functions, basic medication screening had the largest share of health systems reporting use by all their clinics (32% in 2016) and reporting use by some or all their clinics (44% in 2016) (**Figure 2**).

For every CDS function, clinics in multihospital systems (as opposed to single-hospital systems) had an increased likelihood of CDS use, ranging from genomics profiles having a 5.1% increased likelihood to be used in orders in multihospital systems to diagnostic result alerts having a 21.7% increased likelihood to be used in multihospital systems (**Table 2**). Clinic size (clinics with ≥ 4 physicians) was associated with a small to moderate increased likelihood of use for all CDS functions, except remote device alerts, ranging from 2.1% (genomics profiles used in orders) to 10.2% (clinical guidelines or protocols). Type of clinic (primary vs specialty care) was not associated with use of CDS except in use of preventive medicine.

We found similar associations among clinics that were not using CDS in 2014 compared with subsequent use in 2015 or 2016, with higher use among clinics affiliated with multihospital systems and clinics of large size. However, almost all coefficients were lower

compared with the complete panel results (**Table 3**). These findings indicate that the magnitudes of associations between CDS use and these 2 factors (multihospital system affiliation and size of clinic) have decreased over time.

DISCUSSION

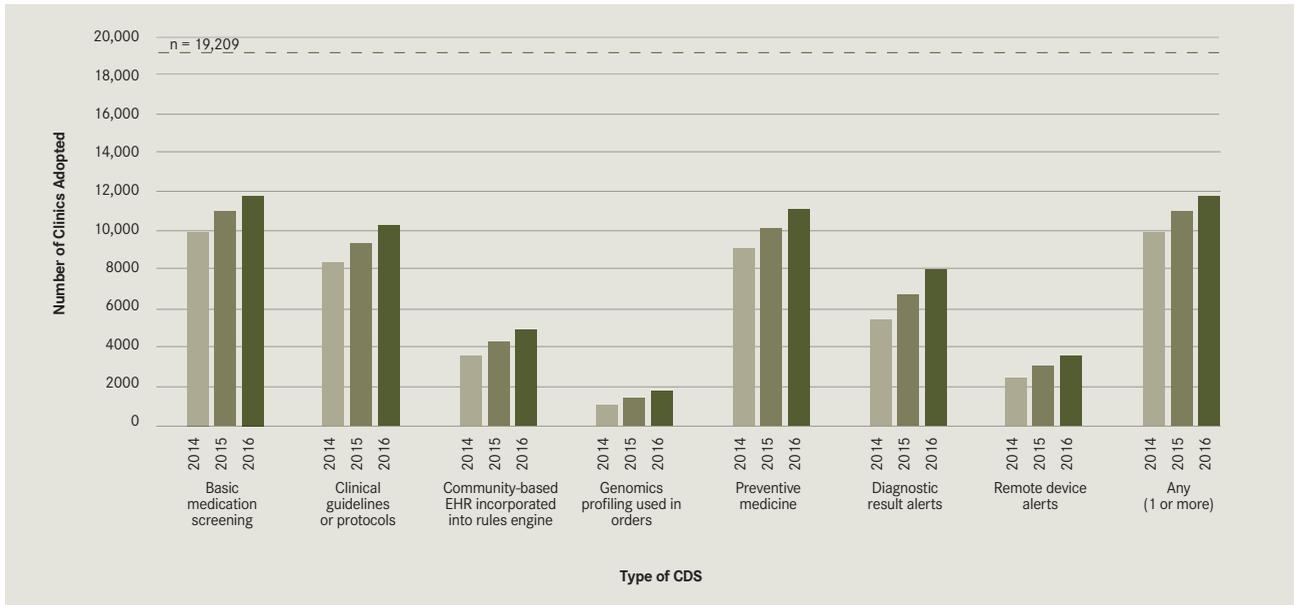
This study of a national panel of health system–affiliated clinics provides a national view of the state of CDS use in the ambulatory care setting during a recent 3-year period. The principal findings are that the use of CDS tools is increasing, particularly in larger clinics and those affiliated with multihospital health systems, but there is wide variation in use by CDS function and considerable room to increase the penetration of all CDS functions. Of health system–affiliated ambulatory clinics, 62% were using 1 or more of the 7 examined CDS functions. The portion of health systems with at least some clinics using 1 or more CDS function was 45%. Considering the public investments in promoting CDS, these levels of use are likely substantially lower than expected.

Multiple factors may explain the variation by CDS function. MU likely promoted some functions of CDS (eg, basic medication screening, preventive medicine) more than others. Feasibility of implementation, availability of best practices, disruption in workflow, and perceived clinical and/or financial benefit by clinicians likely also affect CDS use. The CDS functions with the strongest evidence base (eg, medication screening, clinical guidelines, preventive medicine) seem to have greater use, and there seems to be less use of CDS functions that are not as well studied (eg, genomics profiles used in orders, incorporating community EHR data, remote device alerts).^{5,13}

The substantial association of CDS use with an ambulatory practice affiliation with a multihospital system and clinic size likely reflects the greater number of staff and more resources available for rolling out clinical IT systems in larger health systems and clinics.^{14,15} The weakening over time of the associations of CDS with affiliation with a multihospital system and clinic size may be due in part to MU incentives that promoted CDS more evenly compared with prior years or to a relative increase among single-hospital systems and small clinics in their perceived need to adopt health IT. Even though these associations have weakened over time, they are significant and suggest that single-hospital systems and small clinics may need additional assistance in implementing and using CDS. Further study is needed to better understand the barriers facing single-hospital systems and small clinics and develop solutions to address those barriers.

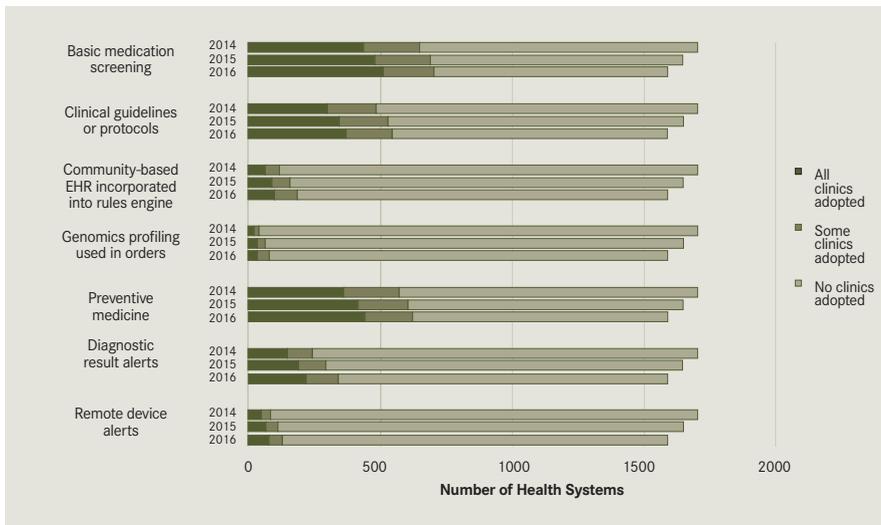
Most nationwide studies of health IT have focused on hospitals.^{11,16–18} To address policy goals of higher quality and lower costs, more attention should be given to ambulatory clinics to ensure that they have the necessary tools to provide optimal care and prevent

Figure 1. Change in the Use of 7 CDS Functions in Health System–Associated Ambulatory Clinics, 2014-2016



CDS indicates clinical decision support; EHR, electronic health record.

Figure 2. Health System–Wide Use of 7 Types of CDS Within Ambulatory Clinics, 2014-2016



CDS indicates clinical decision support; EHR, electronic health record.

ambulatory care–sensitive hospital admissions. Direct incentives may not be effective to achieve universal adoption: Results of one analysis suggest that existing federal incentives have had minimal to no effect on EHR adoption in ambulatory settings.¹⁹ However, there are other policy options, such as increasing the proportion of value-based payment arrangements through payer contracting to provide incentives for the cost and quality outcomes facilitated by CDS;

supporting the development of more usable and implementable CDS capabilities through research or EHR certification requirements; generating additional evidence of the effect of less-used CDS functions on quality, safety, health outcomes, and costs; and promoting and disseminating best practices for implementation and ongoing use.

Vendors and health systems should also play important roles in increasing CDS use. Vendors can prioritize developing CDS functionalities and making them more usable and easier to implement. Health systems can influence their affiliated clinics to adopt CDS tools because they often control the IT systems centrally and can learn and apply best practices for efficiently and effectively implementing these tools in their many clinics.

Limitations

This study had a number of limitations. First, HIMSS data (and therefore the panel of ambulatory clinics) excluded clinics unaffiliated with a health system, and the study is therefore not a complete assessment of the state of CDS use in all ambulatory

Table 2. Association Between Clinic Characteristics and Reported Use of CDS During 2014-2016^a

	Clinic Is Primary Care		Clinic Is Affiliated With Multihospital System		Size of Clinic (≥4 physicians)	
	Estimated Coefficient ^b (95% CI)	P	Estimated Coefficient ^b (95% CI)	P	Estimated Coefficient ^b (95% CI)	P
Basic medication screening	0.028 (-0.0019 to 0.0582)	.066	0.150 (0.0711-0.2280)	<.001	0.099 (0.0637-0.1341)	<.001
Clinical guidelines or protocols	0.028 (-0.0030 to 0.0586)	.078	0.193 (0.1121-0.2740)	<.001	0.102 (0.0638-0.1403)	<.001
Community-based EHR incorporated into rules engine	-0.001 (-0.0340 to 0.0321)	.956	0.128 (0.0503-0.2060)	.001	0.084 (0.0336-0.1336)	<.001
Genomics profiling used in orders	0.002 (-0.0100 to 0.01364)	.764	0.051 (0.0130-0.0882)	.008	0.021 (0.0002-0.0422)	.048
Preventive medicine	0.031 (0.0004-0.0623)	.047	0.159 (0.0801-0.2382)	<.001	0.097 (0.0600-0.1347)	<.001
Diagnostic result alerts	0.003 (-0.0273 to 0.0339)	.833	0.217 (0.1396-0.2936)	<.001	0.085 (0.0421-0.1277)	<.001
Remote device alerts	-0.007 (-0.039 to 0.0264)	.698	0.114 (0.0483-0.1800)	.001	0.050 (-0.0003 to 0.1015)	.052

CDS indicates clinical decision support; EHR, electronic health record.

^aBold indicates $P < .05$.

^bAn estimated coefficient of 0.1 indicates a 10% increased likelihood of reported CDS use.

settings in the United States. Clinics that are not affiliated with health systems likely have different (and probably lower) CDS use patterns because of more limited resources; therefore, our reports are likely an overestimate of the national rate. Second, the data were from a self-reported survey and have not been validated. However, our previous work found high concordance with HIMSS and another survey on some variables.²⁰ Third, CDS use variables were binary and did not include extent or effectiveness of use. Fourth, the analyses assessed associations, not causality with regard to clinic characteristics that may affect CDS use. Fifth, clinics without responses were excluded, so there may be some nonresponse bias.

CONCLUSIONS

Despite substantial federal incentives related to health IT adoption, major gaps remain in the use of many CDS functions among ambulatory clinics, especially among single-hospital systems and smaller clinics. Greater incentives to use CDS to improve care or lower costs, improving availability and usability of CDS capabilities within EHRs, and spreading best practices may help accelerate increased use of CDS in health systems.

Acknowledgments

The authors thank John Daly of RAND for assistance with the data.

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Source of Funding: This work was supported through the RAND Center of Excellence on Health System Performance, which is funded through a cooperative agreement (1U19HS024067-01) between the RAND Corporation and the Agency for Healthcare Research and Quality (AHRQ). The content and opinions expressed in this publication are solely the responsibility of the authors and do not reflect the official position of AHRQ or HHS.

Author Disclosures: The authors report no relationship or financial interest with any entity that would pose a conflict of interest with the subject matter of this article.

Authorship Information: Concept and design (RSR, SHF, YS, PS, DPS); acquisition of data (YS, DPS, CLD); analysis and interpretation of data (RSR, SHF, YS, PS, AA-R); drafting of the manuscript (RSR); critical revision of the manuscript for important intellectual content (RSR, SHF, YS, PS, AA-R, MSR, DPS, CLD); statistical analysis (RSR, SHF); obtaining funding (RSR, MSR, DPS); administrative, technical, or logistic support (MSR); and supervision (MSR).

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Table 3. Association of Health System–Associated Clinics’ CDS Use in 2015 or 2016 With Their Primary Care Status, Affiliation With a Multihospital System, and Size^a

	Clinic Is Primary Care		Clinic Is Affiliated With Multihospital System		Size of Clinic (≥4 physicians)	
	Estimated Coefficient ^b (95% CI)	P	Estimated Coefficient ^b (95% CI)	P	Estimated Coefficient ^b (95% CI)	P
Basic medication screening	0.013 (-0.0215 to 0.0481)	.453	0.111 (0.0287-0.1924)	.008	0.080 (0.0452-0.1140)	<.001
Clinical guidelines or protocols	0.016 (-0.0146 to 0.0458)	.31	0.143 (0.0680-0.2173)	<.001	0.059 (0.0281-0.0901)	<.001
Community-based EHR incorporated into rules engine	0.010 (-0.0121 to 0.0328)	.369	0.054 (0.0079-0.1008)	.022	0.034 (0.0153-0.0530)	<.001
Genomics profiling used in orders	-0.003 (-0.0180 to 0.0111)	.646	0.037 (0.0080-0.0662)	.012	0.020 (0.0030-0.0376)	.022
Preventive medicine	0.021 (-0.0123 to 0.0548)	.215	0.119 (0.0403-0.1978)	.003	0.080 (0.0471-0.1127)	<.001
Diagnostic result alerts	0.020 (-0.0085 to 0.0486)	.170	0.152 (0.0825-0.2224)	<.001	0.062 (0.0318-0.0930)	<.001
Remote device alerts	0.010 (-0.0061 to 0.0261)	.226	0.053 (0.01281-0.0928)	.01	0.028 (0.0068-0.0486)	.009

CDS indicates clinical decision support; EHR, electronic health record.

^aBold indicates *P* < .05.

^bAn estimated coefficient of 0.1 indicates a 10% increased likelihood of reported CDS use.

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Comparison of Healthcare Delivery Systems in Low- and High-Income Communities

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ABSTRACT

Objectives: To compare supply of and access to physicians and hospitals for low- and high-income communities in the United States following the Affordable Care Act.

Study Design: Cross-sectional study using 2015 data on physicians and hospitals from CMS, SK&A, commercial claims, and the American Hospital Association.

Methods: We computed densities of primary care and specialty physicians in low- and high-income zip code tabulation areas (ZCTAs), further stratified by urban, suburban, and rural categories. We also estimated geodetic distances to the nearest general acute care, teaching, children's, and psychiatric hospitals for each ZCTA.

Results: Urban low-income ZCTAs were 0.5% more likely to have very low primary care physician density (<5 physicians per 10,000 population) relative to high-income ZCTAs. The disparity was great in rural areas (where the analogous figure was 1.7%) and greatest in suburban areas, where low-income ZCTAs were 7.4% more likely to have very low primary care density relative to high-income ZCTAs. The percentage of urban and suburban low-income ZCTAs with very low specialty physician density was 1.3 to 1.4 times larger than that of high-income ZCTAs. Although the average distance to a general acute care hospital was similar for low- and high-income ZCTAs (median difference range, 0.4-2.1 miles), residents of rural low-income areas had to travel substantially farther to teaching, children's, and psychiatric hospitals (10.2-35.6 miles).

Conclusions: Our findings document geographic variation in provider supply related to income and suggest that improving access to care may require greater attention to local delivery systems.

The American Journal of Accountable Care. 2019;7(4):11-18

One of the chief goals of the Affordable Care Act (ACA) was to expand access to healthcare to all Americans, particularly through insurance coverage.¹ However, while health insurance increases access to care, it does not guarantee such access.^{2,3} Specifically, the structural aspects of the local delivery system—supply, location, and organization of healthcare resources—all vary widely across markets, but they have received much less attention than coverage as a driver of disparate access. Although considerable literature relates availability of primary care to beneficial outcomes and lower costs,⁴⁻⁷ it does not focus on disparities in access related to income. Although many studies have shown that Medicaid expansions have reduced the number of uninsured Americans,⁸⁻¹¹ few studies have looked at primary care supply after many states' Medicaid expansions took effect in 2014. The effects of improved financial access for disadvantaged populations depend on the nature of their local delivery systems.

Barriers to access posed by lack of healthcare facilities and trained physicians has been well documented.¹²⁻¹⁵ Policies to address scarcity of healthcare resources date back to at least the 1946 Hill-Burton Act. Today, the Health Resources and Services Administration identifies Health Professional Shortage Areas (HPSAs) or Medically Underserved Areas/Populations based on shortage designation criteria that it develops in collaboration with state partners.¹⁶ However, the HPSA definition of a shortage area is based on context and specific applications, not a broad assessment of community needs. While adequacy of the supply of providers for low-income individuals is largely unknown, dependence on local safety net providers is substantial and potentially

Table 1. Socioeconomic Characteristics of US Population in Low- and High-Income ZCTAs^a

Measure	All ZCTAs	Correlation With Percentage Below 200% FPL	Low-Income ZCTAs	High-Income ZCTAs	Low-Income as a Percentage of High-Income ZCTAs
Number of individuals	316,196,416		27,621,556	46,531,012	
Number of ZCTAs	32,322		3232	3232	
Percentage of individuals below 200% FPL	34.4	1.0	64.9	13.8	4.70
Percentage of individuals above 500% FPL	25.5	-0.7	6.6	54.2	0.12
Median household income in \$	52,063	-0.8	26,839	82,518	0.33
Percentage with household income below 100% FPL	15.6	0.8	35.5	5.7	6.23
Percentage receiving SSI	5.4	0.5	10.9	2.5	4.36
Percentage receiving public assistance income	2.8	0.3	6.0	1.2	5.00
Percentage receiving SNAP benefits	13.4	0.7	31.5	3.5	9.00
Percentage black	12.6	0.1	29.2	5.4	5.41
Percentage Hispanic	17.1	0.06	40.0	8.7	4.60
Percentage uninsured	13.0	0.6	22.9	5.9	3.88
Percentage insured by Medicaid	13.7	0.7	29.9	4.3	6.95
Percentage with high school education	86.3	-0.6	69.1	95.3	0.72
Percentage with disability	12.4	0.5	14.7	8.1	1.81
Percentage 16 years or older in labor force	63.8	-0.5	57.7	68.2	0.85
Percentage younger than 18 years	23.3	0.1	27.3	22.7	1.20
Percentage aged 18-64 years	14.1	-0.1	62.5	62.8	1.00
Percentage 65 years or older	64.9	-0.05	10.2	14.5	0.70

FPL indicates federal poverty level; SSI, Supplemental Security Income; SNAP, Supplemental Nutrition Assistance Program; ZCTA, zip code tabulation area.

^aThe table reports weighted averages at the national level and by low- and high-income ZCTA groups. For most of the socioeconomic status measures, there were complete data for all 32,322 ZCTAs included in our analyses. There were missing data for a few of the measures (maximum of 4.3% missing median household income). The correlations between each measure and percentage below 200% FPL were estimated using unweighted data. All correlations were statistically significant at the 0.001 level.

precarious^{17,18}: Today, 1 in 13 Americans obtain care from the 10,000 community health center sites funded by the ACA.¹⁹

Much of the existing literature relating provider supply to outcomes focuses on rural areas. Prior research suggests that rural populations experience greater difficulties in accessing needed care compared with urban populations.²⁰ Rural areas often encounter challenges in attracting and retaining providers because providers feel “overburdened and underpaid,” among other reasons, compared with those in urban areas.^{20,21}

Yet rural is not synonymous with low income, and quantitative analyses of delivery systems in low-income areas are lacking despite the focus on access expansion policies for low-income populations. Existing research on this topic is largely qualitative and in the form of case studies of high-functioning safety net organizations.²²⁻²⁶ The large literature on the safety net generally takes the provider as the

unit of observation and hence cannot speak to differences among communities in access to care associated with the local availability of providers. There has been little research to characterize healthcare delivery systems in low-income communities nationally.

We use a unique relational database to examine potential barriers to access and to quantify variation in the supply of primary care and specialty physicians, as well as general acute care and specialty hospitals, across the United States. In this paper, we present a large-scale, national description of the local healthcare delivery systems found in low- versus high-income communities following the ACA.

METHODS

Zip Code Tabulation Areas

We selected zip code tabulation areas (ZCTAs) as our primary unit of observation, excluding 667 ZCTAs with fewer than 10

residents and 517 ZCTAs with missing income data. Our final database included 32,322 ZCTAs with 316,196,416 residents (99.9% of the US population in 2015).

ZCTAs capture variation in income better than larger units such as primary care service areas (PCSAs). There is often substantial income heterogeneity among the constituent zip codes within a single PCSA, for example. Because individuals may seek care outside of their ZCTAs, we assign to each ZCTA measures of provider supply that encompass a wider area (described below).

Measuring Income

Consistent with previous research^{12,14,27} and using income data from the American Community Survey (ACS), we classified a ZCTA as low-income if the percentage of individuals with income below 200% of the federal poverty level (FPL) fell in the top decile of the national distribution (57.4%-100% population <200% FPL; distributions were computed using all ZCTAs with poverty data and after the population size restriction for metropolitan areas). Analogously, we classified a ZCTA as high-income if the percentage of individuals with income above 500% of the FPL fell in the top decile of the national distribution (43.0%-100% of population >500% FPL). Our results were robust to other thresholds, such as percentage of individuals with income below 100% or below 300% of the FPL.

In a sensitivity analysis, we classified low- and high-income ZCTAs based on their state income distributions and refer to these as relative low- and high-income ZCTAs. Specifically, we classified ZCTAs in each state as being a low- (or high-) income community if the percentage of individuals in the ZCTA with low (high) income fell in the top decile of the state distribution. Income distributions vary from state to state, and relative low-income status in a state may be as important for disparities as national low-income status. Implications for state- and federal-level policy may also differ.

Provider Supply

Physicians. Our data on practicing physicians and their practice locations were derived from 2015 data from the CMS Provider Enrollment, Chain, and Ownership file; SK&A physician file; and CMS MAX Provider Characteristics (verified in the National Plan and Provider Enumeration System) file. The total number of physicians included in this study (n = 818,951) compared favorably with numbers in other sources. The American Medical Association Masterfile contains 829,962 physicians in 2013 and the 2014 SK&A data file contains 565,000 unique physician National Provider Identifiers. Nurse practitioners and physician assistants also deliver care to patients, in some states do not require physician supervision, and sometimes serve as patients' primary care clinicians. However, they were excluded from this study because there was no comprehensive data source on these nonphysician clinicians.

Because some patients cross ZCTA lines for care, we assigned to each ZCTA the physician supply of its PCSA. The ZCTA unit of analysis captures low income more accurately than broader geographic areas, whereas PCSA-level physician supply considers border crossing and more accurately represents the service area in which an individual obtains care. Specifically, we computed primary care and specialist physician density (ie, number of physicians per 10,000 population) for each PCSA and assigned these measures to their corresponding ZCTAs. We counted the 236,575 physicians who practiced at more than 1 site by proportions; for example, a physician who practiced at 2 sites was assigned 0.5 effort at each.

We classified physicians as primary care or specialist. Physicians trained in family medicine, pediatrics, and internal medicine (with no subspecialty training) were classified as primary care physicians. We included only non-hospital-based specialists in our tabulations of specialist supply (ie, not emergency medicine, radiology, anesthesiology, or pathology). Of the 818,951 National Provider Identifiers included in this study, 274,449 (33.5%) were classified as primary care physicians and 396,588 (48.4%) as specialists.

Hospitals. Our hospital data were derived from CMS' Provider of Services file, the American Hospital Association survey, and the SK&A hospital file from 2015. We classified 6337 short-term acute care hospitals into general acute care (n = 5033), children's (n = 187), and psychiatric (n = 2402) hospitals. We identified 1302 (22.0%) teaching hospitals based on the hospital's receipt of graduate medical education payments from CMS in 2015.²⁸ A hospital could be classified as more than 1 type.

We computed 2 measures of the availability of hospital services. First, we computed geodetic distances (shortest curve between 2 points along the surface of the earth) from each ZCTA centroid to the closest general acute care, psychiatric, children's, and teaching hospital. To reduce the effects of outliers, we winsorized the distances at 1% and 99% for each respective type of hospital and geographic category. Second, analogous to how we assigned PCSA data to ZCTAs for physician supply, we assigned to each ZCTA the number of beds (by hospital type) in the Hospital Service Area (HSA) in which it was located. We converted zip codes to ZCTAs and then assigned each ZCTA to an HSA using a zip code to HSA crosswalk from Dartmouth Atlas. A total of 170 ZCTAs could not be assigned to an HSA.

Urban/Suburban/Rural Classification

Building on methods from a previous study and corresponding to geographical distinctions in the Behavioral Risk Factor Surveillance Survey,²⁹ we classified ZCTAs as urban, suburban, or rural (see **eAppendix** [available at ajmc.com]). The proportion of individuals in urban areas was high across both low- and high-income areas (**eAppendix Table 1**). Although it was 10-fold smaller in terms of individuals, rural areas had nearly twice as many ZCTAs as urban

Table 2. Distribution of Primary and Specialty Care Density per 10,000 Population: Number (%) of ZCTAs

	Urban		Suburban		Rural	
	Low-Income	High-Income	Low-Income	High-Income	Low-Income	High-Income
Total ZCTAs	881	864	517	1677	1782	669
Primary care						
<5	771 (87.5)	752 (87.0)	504 (97.5)	1511 (90.1)	1730 (97.1)	638 (95.4)
5-9	89 (10.1)	85 (9.8)	13 (2.5)	124 (7.4)	52 (2.9)	24 (3.6)
10-14	8 (0.9)	17 (2.0)	0	42 (2.5)	0	7 (1.1)
≥15	13 (1.5)	10 (1.2)	0	0	0	0
Specialty						
<5	560 (63.6)	433 (50.1)	476 (92.1)	1080 (64.4)	1711 (96.0)	588 (87.9)
5-9	185 (21.0)	310 (35.9)	30 (5.8)	390 (23.3)	71 (4.0)	53 (7.9)
10-14	77 (8.7)	30 (3.5)	5 (1.0)	139 (8.3)	0	18 (2.7)
15-19	18 (2.0)	31 (3.6)	6 (1.2)	28 (1.7)	0	10 (1.5)
20-24	16 (1.8)	28 (3.2)	0	7 (0.4)	0	0
25-29	7 (0.8)	19 (2.2)	0	11 (0.7)	0	0
30-34	2 (0.2)	13 (1.5)	0	22 (1.3)	0	0
35-39	6 (0.7)	0	0	0	0	0
40-44	1 (0.1)	0	0	0	0	0
≥45	9 (1.0)	0	0	0	0	0

ZCTA indicates zip code tabulation area.

areas. The number of high-income individuals in suburban areas was comparable with that in urban areas, but there were twice as many suburban as urban ZCTAs. Using data from the 2010 US Census³⁰ and rolling 5-year ACS estimates for 2011 to 2015,³¹ we tabulated socioeconomic characteristics for each ZCTA in our sample.

Statistical Analysis

We first compared the distributions of provider supply in low- and high-income urban, suburban, and rural communities. Next, we used weighted linear regression analysis to examine the relationship between the percentage of low-income ZCTA residents and the supply of physicians (in the ZCTA's PCSA) and hospital services (in the ZCTA's HSA).

To assess whether the relationship between physician availability and income varied by urban/suburban/rural designation, we included interaction terms between our measure of low-income (ie, percentage of ZCTA residents with incomes <200% FPL) and urban/suburban/rural indicators. Because physicians affiliated with

hospitals may have a wider service area than the PCSA, we controlled for the presence of a general acute care hospital in the PCSA. If we drop this control, the disparities that we measure are attenuated because low-income areas with general acute care hospitals have higher physician supply (see eAppendix). Standard errors were clustered at the PCSA level.

In a sensitivity analysis, we estimated regressions with state fixed effects to explore whether income-related differences in provider supply operate on a national and/or state level.

RESULTS

Our final data set included 32,322 ZCTAs with 316,196,416 residents: 27.6 million (8.7%) in low-income ZCTAs and 46.5 million (14.7%) in high-income ZCTAs. ZCTAs identified as low-income for this study represent socioeconomically disadvantaged populations with high concentrations of poverty and racial and ethnic minorities and substantially lower rates of health insurance (Table 1).

Low-income ZCTAs were concentrated in the southern region of the United States and high-income ZCTAs in the northeast and mid-Atlantic regions (eAppendix Figure). Low-income ZCTAs were disproportionately located in rural areas (57% compared with 21% of high-income ZCTAs), whereas the majority of high-income ZCTAs were located in suburban areas (52% compared with 16% of low-income ZCTAs). Seventy-six percent of people from low-income ZCTAs and 44% of people from high-income ZCTAs lived in urban areas (eAppendix Table 1).

Physician Disparities

Urban low-income ZCTAs were 0.5% more likely than high-income ZCTAs to have very low primary care physician density (we define this to be fewer than 5 physicians per 10,000 population) (Table 2). The disparity was great in rural areas (where the analogous figure was 1.7%) and greatest in suburban areas, where low-income ZCTAs were 7.4% more likely to have very low primary care physician density. The percentage of low-income ZCTAs in urban and suburban areas with very low specialty physician density was 1.3 to 1.4 times larger than that for high-income ZCTAs (63.6% vs 50.1% in urban areas; 92.1% vs 64.4% in suburban areas).

There was considerable variation within states in both physician supply and rates of low-income ZCTAs (eAppendix Table 2); 82% of total variation in low-income percentage was within states (97% for primary care and 93% for specialty supply). Relative income-related disparities in physician supply might be present if providers chose to locate in higher-income areas within states. To investigate within-state income-related disparities, we added state fixed effects to our regression models. The within-state estimates of

Table 3. Median Distance and Hospital Beds by Income and Urban/Suburban/Rural Classification*

	Urban		Suburban		Rural	
	Low-Income	High-Income	Low-Income	High-Income	Low-Income	High-Income
Number of ZCTAs	881	866	521	1682	1830	684
GAC hospitals						
Median distance in miles to closest GAC hospital	2.2	2.7	6.2	4.7	14.5	12.4
Median GAC hospital beds per 10,000 in HSA	20.3	16.5	16.9	15.4	19.2	17.1
Teaching hospitals						
Median distance in miles to closest teaching hospital	2.7	4.0	21.3	7.7	42.0	28.7
Median teaching hospital beds per 10,000 in HSA	18.6	14.1	13.2	16.7	14.8	15.5
Children's hospitals						
Median distance in miles to closest children's hospital	10.1	9.9	53.5	17.9	85.3	69.9
Median children's hospital beds per 10,000 in HSA	1.7	1.3	1.6	1.9	0.9	0.8
Psychiatric hospitals						
Median distance in miles to closest psychiatric hospital	2.6	3.4	13.4	5.7	28.3	18.1
Median psychiatric hospital beds per 10,000 in HSA	17.3	12.3	14.1	16.4	13.5	14.8

GAC indicates general acute care; HSA, hospital service area; ZCTA, zip code tabulation area.

*The table reports winsorized conditional median distances and beds. Because medians are conditional, there is slight variation in the sample size for each subgroup.

disparities were smaller but still significant for primary care physicians (median density was 27% greater for high-income ZCTAs compared with 50% greater) and specialists in suburban areas (70% greater compared with 147% greater) (eAppendix Tables 2 and 3).

Regressions suggested a significant linear relationship between the percentage of a ZCTA's population with income below 200% of the FPL and the supply of physicians in the ZCTA's PCSA. We plotted the association between ZCTA percent low-income and physician density separately by urban/suburban/rural category (Figure; see eAppendix Tables 4 and 5 for the full set of regression coefficients). In suburban areas, these regression results implied that moving from the 75th percentile of percent low-income (45.8%) to the 25th percentile (23.4%) was associated with an increase in suburban areas of 0.6 primary care and 1.6 specialist physicians per 10,000 PCSA population. The mean percentage of ZCTA residents living below 200% of the FPL was 35.5% (median, 34.2%; SD, 17.1%; range, 0%-100%).

Hospital Disparities

On average, residents in low-income urban areas lived closer to general acute care, teaching, and psychiatric hospitals than residents in high-income urban areas (Table 3). However, differential median distances were large for teaching, children's, and psychiatric hospitals in suburban and rural areas (ranging from 15.6 to 30.7 miles).

We modeled the relationship between the percent of ZCTA residents who were low-income and the distance between the ZCTA's

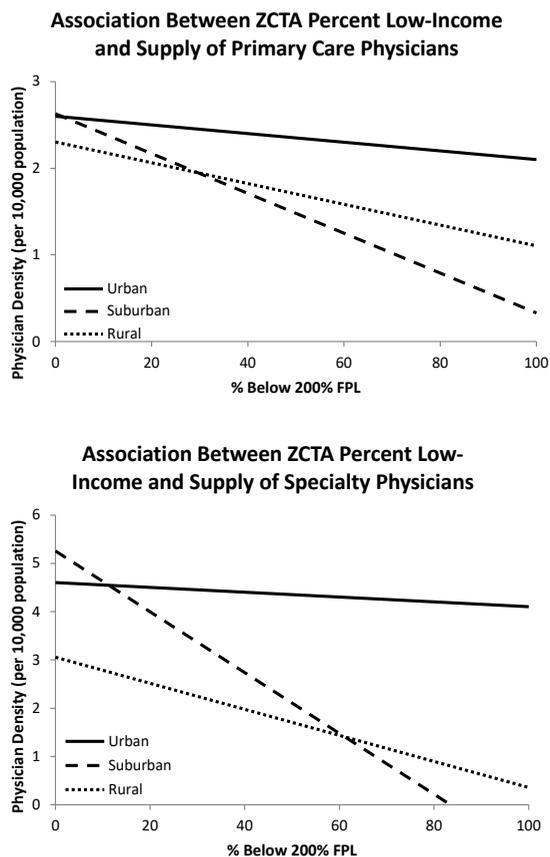
centroid and the closest hospital (eAppendix Tables 6-8). On average, residents of low-income ZCTAs needed to travel 0.5 and 0.2 miles longer to get to the closest general acute care hospital in suburban and rural areas, respectively. Differential distances were similar for teaching, children's, and psychiatric hospitals.

DISCUSSION

In this national study, we documented that physician supply is lower in low- compared with high-income communities and that residents in low-income communities need to travel greater distances to specialty but not necessarily general acute care hospitals. Disparities in physician supply for low- versus high-income communities are greater in suburban areas and for specialty physicians. Disparities were lessened but not eliminated when we examined within-state variation in income and provider supply. Our findings likely underestimate the extent of income disparities in access to healthcare because some physicians do not deliver services to uninsured or Medicaid patients.

Prior work has shown geographic variation in the delivery of healthcare and the importance of the relationship between provider availability and rates of utilization of services such as physician visits.³²⁻³⁴ Provider availability is also related to quality of care.³⁵⁻³⁷ However, much of this work is outdated, and more recent debates on disparities have limited evidence-based discussion of delivery system infrastructure. This study quantifies the current local delivery systems on a national scale by describing the supply of primary care and specialty physicians, as well as access to different types of hospitals. We show that disparities exist between low- and high-income

Figure. Association Between ZCTA Percent Low-Income and Supply of Primary Care and Specialty Physicians



FPL indicates federal poverty level; ZCTA, zip code tabulation area.

communities, particularly in physician supply in suburban areas and in distance to specialty hospitals for residents in rural areas.

Limitations

Our study focuses on one piece of the pathway from access to outcomes (ie, delivery system). Although there is support for this relationship in the literature,³⁸⁻⁴⁰ our lack of claims data prevents us from making connections to outcomes in this paper. We cannot be certain that areas with fewer providers are underserved or that places with more abundant providers are overserved. In addition, it is possible that some of the uninsured, particularly those in low-income, urban areas, utilize emergency department or safety net clinics as a default primary care access point. We did not have these data. Nevertheless, given concerns about primary care shortages generally, we think it is unlikely that residents in low-income communities with access to fewer primary care physicians are optimally served and believe that policies to address health disparities would benefit from greater attention to the local delivery system. Similarly, given the increasing interest among policy makers in

transportation issues for low-income patients, understanding travel distances is important.

There are also measurement issues worth noting. First, defining markets is challenging because patients can cross boundaries. The measurement of disparities in provider supply related to income may be sensitive to how markets are defined and academic medical centers are treated. Large urban medical centers have many academic physicians who see patients on a part-time basis. These centers are mostly located in urban, often low-income, communities and may artificially inflate provider supply estimates. Second, without recent national Medicaid claims data, we could not examine the extent to which being restricted to providers who accept Medicaid contributed to disparities in access. Third, we did not have cost and quality data for comparing within and across urban, suburban, and rural areas. Fourth, because of data limitations, we could not identify all of the sites in which nonphysician providers such as nurse practitioners delivered care, and therefore did not include them in our analyses. Finally, our results are based on averages across all markets, masking much heterogeneity at the local level. Although the heterogeneity within and across local areas may make it difficult to generalize across the United States, this high-level view is important for informing both federal and local policy.

CONCLUSIONS

This study complements other related work. Specifically, recent studies of access focus attention on health insurance expansions (ie, patients' ability to pay for care).^{3,8,10,28,41-45} The 2016 National Healthcare Quality and Disparities report documented income- and race-related disparities in healthcare utilization and quality.¹⁵ A more recent study by Chetty and colleagues went a step further in documenting substantial local area variation in income-related disparities in health outcomes that were uncorrelated with health insurance coverage.⁴⁶ This study on local delivery systems broadens the policy discussion to include nonfinancial barriers to accessing care such as the resources and services available in local communities.

The stratification of our analyses by urban, suburban, and rural areas generated findings consistent with and complementary to those of Schnake-Mahl and Sommers.²⁹ Based on data from a nationally representative survey defining access as having health insurance, a usual source of care, unmet need due to cost, and receipt of a routine checkup, they find that suburban low-income residents face higher barriers to accessing care. Combining their findings with ours suggests that suburban areas may be high-potential places for delivery system interventions to close the divide between the low- and high-income residents. Improving access to care for low-income populations may require greater attention to provider availability and access to specialty hospitals in local delivery systems.

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Source of Funding: Research reported in this study was supported by The Commonwealth Fund under award number 20160683. The content is solely the responsibility of the authors and does not necessarily represent the official views of The Commonwealth Fund.

Author Disclosures: The authors report no relationship or financial interest with any entity that would pose a conflict of interest with the subject matter of this article.

Authorship Information: Concept and design (CAN, MEC, IO, NDB); acquisition of data (CAN, IO, NDB); analysis and interpretation of data (CAN, MEC, IO, NDB); drafting of the manuscript (CAN, NDB); critical revision of the manuscript for important intellectual content (CAN, MEC, NDB); statistical analysis (CAN, IO, NDB); obtaining funding (MEC); administrative, technical, or logistic support (CAN, IO); and supervision (CAN, NDB).

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