The Association of Electronic Health Record Adoption with Staffing Mix in Community Health Centers

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Objective. To assess how medical staffing mix changed over time in association with the adoption of electronic health records (EHRs) in community health centers (CHCs).

Study Setting. Community health centers within the 50 states and Washington, DC.

Study Design. Estimated how the change in the share of total medical staff full-time equivalents (FTE) by provider category between 2007 and 2013 was associated with EHR adoption using fractional multinomial logit.

Data Collection. 2007–2013 Uniform Data System, an administrative data set of Section 330 federal grant recipients; and Readiness for Meaningful Use and HIT and Patient Centered Medical Home Recognition Survey responses collected from Section 330 recipients between December 2010 and February 2011.

Principal Findings. Having an EHR system did significantly shift the share of workers over time between physicians and each of the other categories of health care workers. While an EHR system significantly shifted the share of physician and other medical staff, this effect did not significantly vary over time. CHCs with EHRs by the end of the study period had a relatively greater proportion of other medical staff compared to the proportion of physicians.

Conclusions. Electronic health records appeared to influence staffing allocation in CHCs such that other medical staff may be used to support adoption of EHRs as well as be leveraged as an important care provider.

Key Words. Econometrics, health workforce: distribution/incomes/training, information technology in health, uninsured/safety net providers, administrative data uses

The Affordable Care Act of 2010 (ACA) put a spotlight on primary care by emphasizing the need for better preventive care, earlier symptom detection, and management of population health. Electronic health record (EHR) systems are expected to help meet these needs in primary care settings, especially

as meaningful use criteria put forth by the Office of the National Coordinator for Health IT go into effect. Recent studies have found that EHRs appear to improve provider communication and the quality of patient care (Frimpong et al. 2013; Kern et al. 2015; Morton et al. 2015; O'Malley et al. 2015), but other studies have found mixed results on productivity and costs/revenue (Adler-Milstein, Green, and Bates 2013; Amico et al. 2014; Fleming et al. 2014; Frogner et al. 2017). A recent systematic review of how meaningful use functionalities in health information technology (IT), including EHRs, also found mixed results with regard to quality, safety, and efficiency outcomes; a gap identified by the review that this study aims to partially address is how institutional context such as staffing and organizational changes occurred in response to EHR adoption, and how those changes facilitated the expected outcomes (Jones et al. 2014).

The mixed review of the impact of health IT adoption on outcomes is not necessarily surprising given a rich body of economic literature built on the "productivity paradox" theory developed by Solow (1957). Essentially, the "productivity paradox" is when the expected productivity improvements of new technologies do not materialize. Specifically related to IT, economists have pointed to the fact that we may be measuring the wrong outcomes and may be missing the organizational changes that have other positive impacts that make it worthwhile for managers to invest in IT (Brynjolfsson 1993; Triplett 1999). Among these benefits of IT include the increase in delegation of tasks, greater use of teams, and having flexibility and leverage over the skills of workers (Bresnahan, Brynjolfsson, and Hitt 1999; Brynjolfsson 2000). For example, one qualitative study of clinicians found that health IT allowed providers to work at the top of their license by shifting duties among providers, which providers perceived to have resulted in more efficient delivery of quality care (O'Malley et al. 2015).

For CHCs, these IT benefits may be of particular appeal because CHCs have long operated with low financial resources and have faced challenges in staffing recruitment and retention (Rosenblatt et al. 2006). Further, as

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Medicaid expands, CHCs as a safety net provider may see an increasing volume of patients, which may further exacerbate staffing challenges (Miller et al. 2016). A recent study found that CHCs have been adaptable to these staffing challenges by leveraging the clinical staff available in many different configurations in order to maintain productivity (Ku et al. 2015). Indeed, despite chronic staffing shortages, CHCs have emerged as leaders in the adoption of EHRs among primary care providers helped, of course, by investments from the American Recovery and Reinvestment Act of 2009 (Jones and Furukawa 2014). One such investment was the temporary establishment of Regional Extension Centers (RECs), which provided support to rural providers with external staffing support (Casey, Moscovice, and McCullough 2014). What is not known is whether and how CHCs have changed their internal staffing in response to the adoption of EHRs, which this study investigates.

METHODS

Data

The primary source of data for this study was the 2007–2013 Uniform Data System (UDS), which is the administrative reporting system required by the Health Resources and Services Administration (HRSA) for all CHCs receiving federal Section 330 grants within the 50 states, District of Columbia (DC), and U.S. territories to complete on a calendar year basis (BPHC 2013). In this study, we used the term “community health center” (CHC) to refer to all Section 330 grantees. CHCs are also commonly referred to as a “health center” or “federally qualified health center.” Our UDS data did not include those FQHCs that were sponsored by tribal or Urban Indian Health Organizations, “look-alike” clinics, or Nurse Managed Health Clinic programs unless any of these programs received Health Center Grant funds from Section 330.

For one key variable of interest—year of EHR adoption (described below)—we supplemented UDS with responses from a survey called “Readiness for Meaningful Use and HIT and Patient Centered Medical Home Recognition Survey” (referred to as the “Readiness Survey”). The Readiness Survey was conducted by researchers in the Geiger Gibson Program in Community Health Policy at The George Washington University in partnership with the National Association of Community Health Centers (Cunningham, Lara, and Shin 2012). The goal of the survey was to collect more detailed information than what was available through UDS and in the literature at that time on CHCs’ EHRs status and expected plans for adoption, CHCs’ readiness to

meet meaningful use criteria, and their readiness to achieve Patient-Centered Medical Home (PCMH) recognition. All Section 330 grantees were eligible to participate in the survey. The respondent was a “knowledgeable person” designated by the CEO or Executive Director of the CHC. Data were collected between December 2010 and February 2011. The response rate was 63.5 percent, or 714 CHCs of 1,124 eligible, of which 679 were fully completed. No statistically significant differences in CHC location, size, and patient type were found between the survey respondents and the full population of CHCs (Cunningham, Lara, and Shin 2012). The Readiness Survey has been used in combination with UDS in other studies investigating EHR adoption patterns in CHCs (Shin and Sharac 2013; Frogner et al. 2017).

The outcome variable of interest was the share of total medical staff full-time equivalents (FTEs) in a CHC by four categories of providers that were obtained from UDS: (1) physicians, (2) advanced-level providers (i.e., NPs, PAs, and certified nurse midwives), (3) nurses (including registered nurses, licensed practical and vocational nurses), and (4) other medical staff (including medical assistants, nurse aides, and staff who support quality assurance and/or EHR programs). These categories of medical staff were defined by UDS and could not be disaggregated further. CHCs may employ many other types of staff that play an important role in health care delivery, including mental health providers, oral health providers, and enabling staff, but these services have been growing over time and were not delivered across all CHCs. For this study, we focused on staffing related to medical services because these services were provided at nearly every CHC, which provided consistency across the sample and maximization of sample size.

In UDS, staff time was allocated by their functions. If a person was hired full time for clinical purposes, then all of their time was classified as FTE as a medical staff member. If this person conducted some administrative or non-clinical roles, but was not specifically hired in these roles, then his or her time was still allocated to medical staff FTEs. The time of a person hired for multiple roles was allocated based on the percent effort spent in that role; for example, if a person provided medical services for 75 percent of his or her time and enabling services for 25 percent of the time, then 75 percent of the person’s time was reported as medical staff FTE and 25 percent was reported as enabling staff FTE. Missing staff data were imputed based on CHCs with available data using ordinary least squares estimating FTE within a category of providers as a function of years.

The key explanatory variable was whether a CHC had an EHR system within a given year. To identify the year in which a CHC adopted an EHR

system, we relied on the UDS in combination with the Readiness Survey. The Readiness Survey first asked of CHCs, “Does your organization use an electronic health record?” Among those that said yes, CHCs were asked, “How long ago did your organization go live with the EHR?” For the second question, the response choices (and our assumed year of adoption) were <6 months (2010), 6–12 months (2010), 1–2 years (2009), 3–4 years (2007–2008), 5 or more years (prior 2007), and not sure (unassigned year). We assigned CHCs that stated they adopted prior to 2007 as “always had EHRs.” For those who answered “no” to the first question, but answered “yes” to the 2011 UDS question “Does your Center currently have an Electronic Health Record (EHR) system installed and in use?” were assumed to have adopted an EHR system in 2011. Similarly, CHCs that stated “no” to this 2011 UDS question but stated “yes” to the same question in 2012 UDS were assumed to have adopted an EHR system in 2012; and same again for 2013. We assigned CHCs that stated “no” to this question in the 2013 UDS as “never had EHRs.” We assigned CHCs that adopted EHRs between 2007 and 2013 as “EHR adopters.” Although most CHCs had an identifiable year of EHR adoption including 533 that were identified using the Readiness Survey, a year could not be identified for 267 CHCs. These CHCs had EHR systems in place as of the 2011 UDS, but we did not know in what year they adopted their system and excluded these CHCs from the analysis.

We included a limited number of control variables which were known predictors of health facility staffing (Ku et al. 2015; Frogner et al. 2017) and varied over time such as size/volume of the facility, which we proxied with a binary variable for whether the CHC had greater than the median number of patients seen for medical visits; whether the CHC was located in a rural region of the country; and the local market conditions including the number of active physicians (MDs and DOs) and number of NPs (with a national provider identifier) per 1,000 people by county, as well as whether the whole county was designated as a Primary Care Health Professional Shortage Area by HRSA (BHW 2015). CHC size and rural designation were obtained from the UDS. The local market condition variables were obtained from the Area Health Resource File (AHRF), which is a publicly available health data system provided by the Health Resources and Services Administration (HRSA). AHRF pulls data from other secondary sources and then releases the data annually at the county-level unit of observation. We also tested a broad set of patient characteristics collected from the UDS and controls for state scope of practice restrictions for NPs for further sensitivity analysis.

To identify the impact of patient-centered medical homes (PCMHs) adoption on CHC productivity over time, we also tested models that controlled for the presence of PCMH (BPHC, 2015), which emerged over the later part of the study period and may have impacted staffing. Given that 25 percent of our study sample was missing information on PCMH, we only tested models controlling for presence of PCMH as part of our sensitivity analysis. Worth noting is that not all CHCs that have an EHR are required to be a PCMH, and not all PCMH are required to have an EHR.

Over the study period, there were 1,241 CHCs in total. We excluded 219 CHCs which were not in existence across the entire study period, 28 that were not within the 50 United States or District of Columbia, 4 that did not have information available on the key variables consistently over the study period, and 267 that did not have an identifiable year of EHR adoption. We compared the excluded 267 CHCs against the study sample (Table 1 in Appendix SA2). The study sample had a patient population that was significantly more likely to be young, Hispanic, mixed or unknown race, receiving Medicaid or other public insurance, and at the poverty level or below. The final sample size was 722 CHCs.

Empirical Approach

This study used a fractional multinomial logit (fmlogit) model, which uses a quasi-maximum likelihood function. A fmlogit function allows one to examine how proportions shift between multiple categories, assuming that the proportion across categories add up to one. This function examines how a change in the proportion of one type of provider category such as physicians shifts the proportion of another type of provider category such as nurses, keeping all else constant. The fmlogit approach is different from estimations of FTE, which do not explicitly take into account any constraints to staffing.

In this study, the fmlogit was operationalized by predicting the share of multiple categories of staffing simultaneously relative to an omitted category of staffing (in this case, we used physicians as the omitted category or in other words, comparison group) as a function of year (which allows for prediction for CHCs who never adopt EHR), presence of EHR interacted by year, whether the CHC had a larger patient population than the median CHC or not, whether the CHC was located in a rural area or urban area, and local market conditions. For sensitivity analysis, we tested the presence of PCMH interacted by year, EHR and PCMH dummies, and the interaction between EHR

and PCMH to allow for potential multiplicative effects. This study treated each CHC within a particular year as a unique observation for a total N of 4,857 CHC-year observations (722 unique CHCs).

The coefficients from the fmlogit model are interpreted much like a regular multinomial logit. Coefficients reflect the relative change in medical provider category relative to the omitted provider category (in this case physicians) for a unit change in the independent variable. Due to the challenging nature of multinomial logit models, interpreting the coefficients directly masks the potential significant differences in the time trends within a provider category as it relates to EHR adoption. As such, this study presented the predicted share of staffing within each year by whether the CHC had an EHR system within that year. The point estimates within that year were then tested for statistical significance using a two-sample t -test, and they are presented in the Results section below.

RESULTS

CHC Characteristics

Looking at the baseline (2007) characteristics of CHCs in Table 1, there were significant differences between the three groups of adopters whereby CHCs that never adopted EHRs were notably different than EHR adopters and CHCs that always had EHRs, which were more similar in characteristics. CHCs that never adopted EHRs were more likely than other CHCs to have patients who were male, younger, uninsured, not on Medicare or private health insurance, had limited English proficiency, and were at or below the poverty level; these characteristics of CHCs that never adopted an EHR were similar to those that were excluded from our analysis. CHCs that never adopted an EHR were also more likely to be smaller. In 2009 and 2010, <10 CHCs had adopted PCMH. By 2013, 170, or 23.5 percent, of CHCs in our study sample gained PCMH recognition.

EHR Adoption Patterns

At the beginning of the study period, only 11.5 percent of the 722 CHCs had an EHR system (Figure 1). By the end of the study period, 95.7 percent of CHCs had an EHR system. Over the 7-year study period, 83 CHCs entered the study period with an EHR (i.e., adopted an EHR system prior to 2007), which we referred to as “always had EHRs”; 32 did not adopt an EHR by the

Table 1: Baseline (2007) Community Health Center Profile by Electronic Health Record Adoption Status

	<i>Never Adopted EHRs</i> (<i>N</i> = 32)	<i>EHR Adopter</i> (<i>N</i> = 612)	<i>Always Had</i> <i>EHRs</i> (<i>N</i> = 83)
Female**	51.1%	58.0%	58.5%
Age			
Age 18 and under*	38.6%	35.1%	34.5%
Age 19–64*	65.7%	68.2%	59.9%
Age 65 and over***	7.7%	8.0%	8.2%
Ethnicity			
Hispanic	26.9%	25.4%	25.9%
Race (including Hispanic)			
White	56.5%	54.0%	49.3% ⁰
Black	16.4%	21.7%	18.8%
Asian/Pacific Islander*	1.2%	2.6%	5.6%
American Indian/Alaska Native	8.2%	2.5%	1.9%
Other/unknown*	24.7%	25.0%	26.3%
Insurance type			
Uninsured	54.2%	43.2%	37.2%
Medicaid	25.5%	30.4%	32.6%
Medicare***	6.7%	9.7%	10.3%
Other Public	1.7%	2.0%	2.0%
Private***	16.9%	18.1%	19.9%
Patients with limited English proficiency	26.5%	19.7%	21.3%
Patients at 100% or below poverty level*	53.9%	49.5%	50.6%
Total number of patients (thousands)**	11,894	15,462	21,292
Rural (non-metro)	54.8%	49.2%	38.6%
Located in Health Professional Shortage Area (measured by whole county)	38.7%	53.0%	44.6%
Local market conditions			
Total active physicians per 1,000 population*	3.6	2.9	3.6
Total nurse practitioners w/national provider identifier per 1,000 population**	0.5	0.3	0.3

Note. Analysis of variance was used to test for significance across categories of EHR adoption status; categories may not sum to 100% due to imputation of patient characteristics.
*** $p < .001$, ** $p < .01$, * $p < .05$.

end of 2013, which we referred to as “never adopted EHRs”; and 612 CHCs adopted at some point over the study period.

Regression Results

From the fractional multinomial logit model, the coefficients for the key independent variables of interest, EHR and the interaction between EHR and

Figure 1: Share of Community Health Centers Adopting Electronic Health Records, 2007–2013 ($N = 722$)

year, were statistically significant at $p < .01$ in comparing each category of staffing to physicians with the exception of the interaction of EHR and year for other medical staff; year alone was not statistically significant (Table 1 in Appendix SA2). In other words, having an EHR system significantly shifted the share of workers over time between physicians and each of the other categories of health care workers, but this effect did not significantly vary over time.

Among our control variables, being located in a rural area significantly influenced the distribution of medical staff, such that CHCs in rural areas tended to have a higher share of advanced-level providers and nurses, but a lower share of other medical staff relative to their urban counterparts. Larger CHCs tended to have a lower share of advanced-level providers and higher share of nurses and other medical staff compared to smaller CHCs. Having more physicians present in the local market significantly decreased the share of advanced-level providers, nurses, and other medical staff and increased the share of physicians on staff. Having more NPs in the local market increased the share of advanced-level providers and nurses but decreased the share of other medical staff. When we included controls for PCMH in our sensitivity analysis, the coefficients were not statistically significant and the fmlogit predicted shares maintained similar patterns; similarly, in further sensitivity testing, including a broad set of patient characteristics (e.g., insurance status, race, language proficiency) and state scope of practice laws for NPs had mixed statistically significant results, and the fmlogit patterns remained consistent (data available upon request).

As shown in Figure 2, the general trends suggest that regardless of EHR implementation, the mix of medical staff had been shifting away from physicians, and slightly more toward advanced-level providers. Looking along the *x*-axis (years) in Figure 2, CHCs were moving from the “no EHR” into the “yes EHR” line; as such, we were able to interpret the trends according to how earlier adopters (loosely defined as pre-2010) staffed their CHCs versus later adopters (loosely defined as post-2010). Earlier adopters of EHRs tended to have a significantly smaller share (1–2 percent at $p < .001$) of physicians on staff versus CHCs that did not adopt EHRs yet. While the gap closed over time, the trends reversed such that the remaining CHCs that did not adopt an

Figure 2: Predicted Shares of Staffing Type by Adoption of Electronic Health Records in Community Health Centers

Note. EHR, electronic health record; predicted estimates are from fractional multinomial logit model controlling for EHR dummy, whether the CHC had greater than the median number of patients seen for medical visits, whether the CHC was located in a rural area, number of physicians, and nurse practitioners per thousand capita in county. p -Values based on t -test between estimates. *** $p < .001$, ** $p < .01$, * $p < .05$.

EHR by 2013 had a significantly ($p < .01$) smaller share of physicians on staff. Earlier adopters of EHRs had no significant differences in staffing of advanced-level providers and nurses. CHCs that remained without an EHR in later years had significantly ($p < .01$ and $p < .001$) higher proportions of advanced-level providers and nurses on staff. CHCs that had an EHR, regardless of being an early or late adopter, consistently had a significantly ($p < .05$, $p < .01$, and $p < .001$) higher proportion of other medical staff; the remaining CHCs that had yet to adopt an EHR by 2013 had approximately a 6 percentage point difference in the share of other medical staff than CHCs that had adopted by 2013.

Limitations

This study has a few limitations to consider. First, our study is observational. We were only able to show the association of staffing patterns with EHR adoption, rather than show causal influence of EHRs on staffing patterns. Second, we did not have full-time series information on when EHR adoption and had to exclude 267 CHCs from the analysis. We found that the excluded sample who had EHRs as of 2011 but with an unknown year of adoption were slightly older, less likely to be on Medicaid or other public insurance, and less likely to be at or below poverty; thus, our results may be slightly biased toward CHCs treating a patient population facing tougher financial and possibly health challenges. Third, while UDS provides the largest sample of CHCs, the nature of administrative data did not allow for a comprehensive look at EHRs and workforce. For example, we were not able to assess how providers interacted with EHRs and how this influenced their roles or tasks. We also were not able to assess how quality of care was changing relative to these staffing changes.

CONCLUSION

This study found evidence that CHCs with EHRs appear to have different staffing arrangements of their medical staff FTEs than CHCs without EHRs. Although not conclusive, this study supports the hypothesis that EHR adoption in CHCs allowed for greater flexibility among staff types. Our findings suggest that CHCs with EHRs relied on more FTE of other medical staff compared to other types of medical staffing.

Both groups of CHCs, that is, those with and without EHRs, experienced similar trends over time with a declining share of physicians on staff,

and slightly increasing share of advanced-level providers on staff. Ku and colleagues (under review for HSR special issue) also noted this downward trend in share of physicians on staff at CHCs, but also noted that the total FTE for physicians increased. This trend suggests that total FTE of all medical staff has been growing, but the physician share has been declining while other types of staff were ramping up at a faster pace which was also noted by Ku and colleagues (under review of HSR special issue).

Earlier EHR adopters had a significantly lower share of physicians on staff, but trends reversed in later years. Given that this study was only able to investigate associations, one possible reason for this trend may be that having a strong physician presence was necessary for pushing forward the adoption of EHRs. Later adopters of EHRs and those who remained without an EHR system by the end of the study period had significantly higher shares of advanced-level providers and nurses. While the reasons are not clear for this trend, looking at the characteristics of CHCs that never adopted an EHR system by the end of the study were serving a patient population that may be facing more financial and, as a result, possibly more health challenges, and may not have had the available support staff time or skills to adopt an EHR system. In particular, the consistently high share of other medical staff confirms studies that suggest that adequate support staff is necessary to get an EHR system to successfully “go live” (Frogner et al. 2017). Future research needs to rigorously assess, perhaps in a randomized controlled trial, how the deployment or roll-out of new major features of an EHR impacts the deployment of their medical staff relative to the EHR, and to what extent EHRs are complementing with or substituting for their skills.

The underlying dynamics of the time trends are complex and should continue to be explored in future studies. Changes in staffing over time in any health care environment involve a complex set of decision points. CHCs must balance the availability of providers in the local region, financing, and needs of the patients. There also may be economy- and health care industry-wide changes, such as the deep economic recession, that may be impacting changes in provider availability in local markets and influencing the shift in workers. Generally, during economic recessions, the health care industry has seen growth in employment and in health care utilization (Wood 2011; Ruhm 2013), and health care workers such as registered nurses delayed retirement to ensure sufficient income while their spouses may have been laid off (Auerbach, Buerhaus, and Staiger 2014). In this study, it is impossible to know whether these shift were due to, for example, lack of available physicians, task shifting, increased need for lower skilled work, and/or decisions by workers to

stay in their place of work (Auerbach, Buerhaus, and Staiger 2014). More work is needed to understand why this shift has been occurring. Also, further study is needed to understand how CHC leadership make staffing decisions in response to major system transformations such as EHR adoption, and how that may lead beneficial changes in care delivery that may not be immediately obvious in health outcomes.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Appendix SA2: Supplemental Tables.

Table 1: Comparison of Baseline (2007) Community Health Center Profile of Included versus Excluded Sample.

Table 2: Fractional Multinomial Logit Regression Coefficients on Independent Variables Estimating Share of Each Type of Staffing ($N = 4,857$).