THREE ESSAYS ON RURAL HEALTH ECONOMICS

By

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THREE ESSAYS ON RURAL HEALTH ECONOMICS

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Abstract: Rural hospitals in the U.S. have been struggling financially for the past few decades. The increased number of rural hospitals in financial distress has led to an acceleration in rural hospital closures. Rural hospital closures have become a source of concern for policymakers and researchers, since areas with the highest number of closures tend to be some of the country's most vulnerable ones. Decreased access to care caused by rural hospital closures only worsens health outcomes in already vulnerable sectors of the population. Considering how relevant the rural hospital closure problem has become, there has been a newfound interest in finding solutions to improve rural hospital finances and ultimately avoid closure. The three chapters below explore how distinct hospital-specific and community characteristics influence rural hospital finances and closure. The first chapter examines the relationship between Electronic Health Record (EHR) functionality and hospitals' operating costs, finding that increased EHR functionality is associated with significant decreases in costs, but only for urban hospitals. The second chapter explores whether community sociodemographic factors are associated with the survival or closure of rural hospitals, finding that rural hospitals at risk of financial distress are more likely to experience closure if their communities have higher unemployment rates and higher percentages of their population uninsured. Finally, the third chapter studies the relationship between telehealth / remote patient monitoring implementation before the COVID-19 emergency declaration and revenue changes during the COVID-19 pandemic (from 2019 to 2020), finding that telehealth implementation prior to the COVID-19 pandemic is significantly associated with increases in revenue during the COVID-19 pandemic. Our analyses shed light on the rural hospital closure issue by finding factors associated with decreases in hospital operating costs, decreases in the likelihood of hospital closure, and increases in hospital revenues.

Note: The first chapter in this dissertation is based on an article currently accepted for publication (but not yet in print). A reference (publication date forthcoming) is listed below. The paper is being published "open access" by Thieme Medical Publishers, who publishes the journal Applied Clinical Informatics. This open access option allows "anyone to freely read, download, distribute, and make the article available to the public." Payment for this option was completed on 5/26/2022. I have permission from my co-authors to use the work listed below in my dissertation.

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CHAPTER I

HIGHER ELECTRONIC HEALTH RECORD (EHR) FUNCTIONALITY IS ASSOCIATED WITH LOWER OPERATING COSTS IN URBAN – BUT NOT RURAL – HOSPITALS

Citation: Rhoades, C.A., Whitacre, B.E., and A.F. Davis. 2022. "Higher Electronic Health Record Functionality Is Associated with Lower Operating Costs in Urban—but Not Rural—Hospitals." *Applied Clinical Informatics* 00: 1-16. (Pending publication)

Abstract

The objective of this study is to examine the relationship between EHR use / functionality and hospital operating costs (divided into five subcategories), and to compare the results across rural and urban facilities. To do this, we match hospital-level data on Electronic Health Record (EHR) use / functionality with operating costs and facility characteristics to perform linear regressions with hospital- and time-fixed effects on a panel of 1,596 U.S. hospitals observed annually from 2016 to 2019. Our dependent variables are the logs of the various hospital operating cost categories, and alternative metrics for EHR use / functionality serve as the primary independent variables of interest. Data on EHR use / functionality are retrieved from the American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology (IT) Supplement, and hospital operating cost and characteristic data are retrieved from the American Hospital Directory (AHD). We include only hospitals classified as "general medical and surgical," removing specialty hospitals. Our results suggest, firstly that increasing levels of EHR functionality are associated with hospital operating costs reductions. Secondly, that these significant cost reductions are exclusively seen in urban hospitals; with the associated coefficient suggesting cost savings of 0.14 percent for each additional EHR function. Thirdly, that urban EHR-related cost reductions are driven by general / ancillary and outpatient costs. Finally, that a wide variety of EHR functions are associated with cost reductions for urban facilities, while no EHR function is associated with significant cost reductions in rural locations.

Keywords: electronic health records, hospital costs, rural hospitals, urban hospitals.

1. Introduction

The U.S. health care system is one of the most advanced in the world, but it is also uncoordinated and fragmented, leading to inefficient resource allocation and rising costs (Berwick and Hackbarth, 2012; PricewaterhouseCoopers' Health Research Institute, 2014). Since 2010, 120 rural hospitals have closed and many closed facilities have excited with operating costs exceeding revenues (Kaufman et al., 2016; Topchik et al., 2020). The trend in rural hospital closure is a source of concern because the areas with the highest number of rural hospital closures are some of the country's most vulnerable ones (Hsia, Kellermann, and Shen, 2011; Thomas, Holmes, and Pink, 2016). Considering the rising operating costs and the toll these costs have on rural hospitals, policymakers have long been interested in finding solutions to mitigate them. Since the mid-2000s, analysts have argued that Electronic Health Records (EHRs) is one cost-reducing strategy that could help (Wang et al., 2003; Ford, Menachemi, and Phillips, 2006; Payne et al., 2013).

Electronic Health Record (EHR) is an expression that includes a range of information technologies used to collect information about patients, treatments, and outcomes (Häyrinen, Saranto, and Nykänen, 2008). Proponents believe that EHRs should increase health care quality and reduce operating expenses. Hypothesized improvements that could be translated into cost savings for hospitals include reducing errors, improving the flow of information, and performing the same task with fewer resources (Girosi, Meili, and Scoville, 2005).

From a theoretical perspective, EHR systems could impact dominant input costs (labor and equipment) by improving decision making and offering decision support for treatment plans. This would raise physician efficiency and lower duplicative or problematic medication costs (Borzekowski, 2009). Alternatively, EHRs can help reduce incentives for doctors or patients who wish for more (potentially costly) care, even when the costs are significantly higher than the benefits. They could also reduce labor costs by removing unnecessary outsourced activities like advanced diagnostics, or by changes in workflow that could remove part-time labor. Early studies estimated that EHR adoption could reduce annual health spending by \$78 - \$81 billion (Hillestad et al., 2005; Walker et al., 2005). However, a more in-depth review of the literature on the relationship between EHRs and hospital operating costs is more inconclusive. There are studies that find that EHR adoption *increases* hospital costs (Sidorov, 2006; Furukawa, Raghu, and Shao, 2010; Teufel et al., 2012; Atasoy, Chen, and Ganju, 2018), studies that find that EHR adoption *reduces* hospital costs (Amarasingham et al., 2009; Borzekowski, 2009), and studies that find mixed results (Himmelstein, Wright, and Woolhandler, 2010; Agha, 2014; Dranove et al., 2014; Jones et al., 2014; Highfill, 2020).

The existing literature on the relationship between EHR and hospital costs is also largely missing a comparison of rural and urban facilities. This comparison is an important contribution of our paper, because expectations for EHR impacts across the rural / urban spectrum have not been established. Several studies have explicitly noted the differences in EHR implementation and use in rural vs. urban hospitals. These studies found that smaller staff (and fewer resources generally) in rural locations led to insufficient system / process knowledge – made more difficult by tight implementation schedules (Craven et al., 2014) – and that rural hospitals were seventy-one percent less likely to consider cost reductions as a potential benefit of EHRs (Houser, Au, and Weech-Maldonado, 2011). An additional study found that barriers to integrating EHRs with decision making tools were dramatically different in rural vs. urban locations (Puccinelli-Ortega et al., 2022). The existing literature clearly notes the cost differences that exist between rural and urban hospitals, with an early study finding that case mix and wage rates are important determinants (Cromwell et al., 1987), while more recent work found that bed counts were predictive of costs per adjusted patient day (Coyne et al., 2009). This body of evidence clearly finds rural – urban hospital discrepancies in both EHR implementation and cost structure generally, but no studies we are aware combine these two components.

We also note that a significant amount of prior research mostly focused on the *adoption* of EHRs. These adoption-focused studies observe whether an EHR system is in place at a particular time, with limited insight into its abilities or usage. Such data do not provide insight into the increased functionality of EHR over time, which could better inform the contributions of specific EHR components on operating cost efficiency. We propose that the debate about EHRs should be reframed by focusing on the effect of EHR *functionality* or *use* on hospital costs, as opposed to simple adoption. Several recent studies have found that there is significant variation in how hospital employees use EHRs as part of their daily workflow, with some noting the pervasiveness of "workarounds" (Assis-Hassid et al., 2019); while others found high physician satisfaction with certain functionalities (decision support, test management), but dissatisfaction with others (referral management, discharge forms) (Schopf et al., 2019). One earlier study found that the ability to add new modules or functions was an important option to support workflow needs (Silow-Carroll, Edwards, and Rodin, 2012). These studies help set the stage to address the question of whether increased EHR functionality is associated with better workflow / lower costs – and whether this connection holds in both rural and urban locations.

2. Objectives

This study examines the relationship between EHR use / functionality and hospital operating costs, over time, using varying metrics for EHR use / functionality. We perform linear regressions with hospital- and time- fixed effects on a panel of 1,596 U.S. hospitals observed annually from 2016 to 2019. Our dependent variables are the logs of hospital operating costs (broken into five sub-categories), and alternative metrics for EHR use / functionality serve as the primary independent variables of interest. Our specification controls for the main hospital characteristics expected to impact costs, such as the total number of employees and discharges, and case mix. We run separate regressions for hospitals in rural vs. urban locations to determine whether rural status impacts the EHR / cost relationship.

3. Data

We match hospital level data on EHR adoption / functionality / use from the American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology (IT) Supplement with cost data from the American Hospital Directory (AHD) for the years 2016 – 2019. The AHA IT Supplement contains data on the hospital's EHR system along with metrics that detail the adoption, functionality, and use of EHRs within the hospital. These data have been used to document EHR access and use by federal government organizations and by academic researchers (Charles, Gabriel, and Furukawa, 2013; Adler-Milstein et al., 2014; Walker and Diana, 2016; Adler-Milstein et al., 2017; Parasrampuria and Henry, 2019). AHD is a private company that provides data from hospitals nationwide, using public and private sources. AHD data has also been used in recent academic research (Brewster et al., 2019; Sharma et al., 2020).

We include only hospitals classified as "general medical and surgical", removing specialty hospitals. The final product of our data aggregation is a panel dataset of 1,596 hospitals with information on both hospital operating costs, and EHR adoption / functionality / use for all four years of the analysis. Rural hospitals were identified based on the Federal Office of Rural Health Policy's list of rural zip codes (Health Resources and Services Administration, 2020). Forty-one percent of the hospitals in our dataset reside in a rural location. The main variables of interest are hospital operating costs (broken out into five sub-categories discussed below), and EHR adoption / functionality / use.

The AHD database breaks total hospital operating costs into five sub-categories: general / ancillary, inpatient, outpatient, other reimbursable, and other general services costs. This data comes from the Medicare Cost Reports, namely worksheets A, B, and C (American Hospital Directory, 2021). Notably, EHR related costs are included as "Capital Related Costs" on worksheet B (part of general / ancillary) so that EHR improvements are captured in the cost data. AHD contains annual data for over 7,000 U.S. hospitals, but we link only to those 1,596 completing all four years of the AHA IT survey. The AHD data contain hospital characteristics likely to influence hospital operating costs that can serve as control variables (American Hospital Directory, 2021). This includes the number of beds, employees, discharges, acute days and Case Mix Index (CMI), which has been shown to be an important contributor to hospital operating costs (Watts and Klastorin, 1980; Hay, 2003; Wu et al., 2014).

Our primary independent variables of interest relate to EHR adoption, functionality, and use. The AHA IT database includes several measures that can serve this purpose, with the three we focus being defined below.

(1) Adoption: a dummy variable for the presence of a certified EHR.
(2) Functionality: assigned values 0-27 for the number of computerized system functionalities that are "fully implemented across all units." The computerized system functionalities are divided into five sub-categories: electronic clinical documentation, results viewing, computerized provider order entry (CPOE), decision support, and other functionalities.

(3) Use: assigned values 0-10 for the number of processes or products generated using the EHR system (for example, creating an individual provider performance profile).

The AHA IT survey questions used to derive these measures are provided in Appendix 1A, and the computerized system functionalities comprising the five sub-categories are listed in Appendix 1B.

4. Methods

To examine the relationship between EHR and hospital operating costs, we need to isolate the effect of the EHR metrics (adoption / functionality / use) on hospital operating costs from alternative effects related to hospital characteristics and time trends. We follow Atasoy et al. (2018) in estimating a panel regression with hospital- and year- fixed effects on our panel of hospitals observed annually from 2016 to 2019:

$$logcost_{it} = \boldsymbol{\alpha X_{it}} + \theta EHR_{it} + \tau_t + \mu_i + \varepsilon_{it} \tag{1}$$

where $logcost_{it}$ is the log of hospital operating costs for hospital i in year t, $\boldsymbol{X_{it}}$ are the controls for hospital characteristics that change over time (log of number of beds, log of total employees, log of total discharges, log of total acute days, and case mix index); τ_t captures the average changes to hospital operating costs over time, μ_i is a hospital fixed effect; EHR_{it} can be modified to include any of the three EHR metrics described above; and ε_{it} is the independent random error term.

Our main parameter of interest is θ, with the hypothesis that it will be negative and statistically significant only for EHR functionality (metric 2) and/or use (metric 3). The fixed effects model allows us to account for individual heterogeneity (i.e. hospital-specific effects such as employee attitude towards EHRS) and year effects (capturing any national health care shock or trend) to assess the net impact of the predictors on the outcome variable.

Initially, we employ three fixed-effects panel regressions with the log of total hospital operating costs as the dependent variables and our three metrics for EHR (adoption / functionality /

use) as the main independent variables of interest. We explore these specifications across subsets of rural and urban hospitals. Subsequently, we perform three additional fixed-effects panel regressions using the log of each dominant cost sub-category as dependent variables to inform us about the specific types of costs that seem to be most responsive to EHR functionality. Finally, we explore which of the EHR functionalities (subcategories of metric 2; detailed in Appendix 1B) are most related to the cost sub-categories of interest, and whether these relationships hold across rural and urban geographies.

Our sample is limited by hospitals completing all four years of the IT supplement survey. Since self-selection may occur, to generalize our results we follow Parasrampuria and Henry (2019) and use a logistic regression model to predict the propensity of AHA IT survey response for all four years as a function of hospital characteristics, including size, ownership, type of facility, Case Mix Index, and urban status. Hospital-level weights are derived by the inverse of the predicted propensity, and used in our analysis. Detailed information regarding the logistic regression model is provided in Appendix 1C and Appendix 1D.

Given the panel nature of our data and the evident differences in hospital sizes, costs, and EHR use / functionality between rural; and urban hospitals that we observed in the data section, the presence of heteroskedasticity is likely. To test for groupwise heteroskedasticity in the fixed-effects regression models we perform a Modified Wald test. To test for nonlinearity we use the command NLCHECK in STATA (Jann, 2008).

5. Results

Figure 1.1 demonstrates the significant variation in costs for rural vs. urban hospitals in our sample, with total costs being seven times higher in urban locations. It also highlights an increase in costs over time (particularly for urban hospitals), suggesting that controlling for time-dependent cost increases is an important part of our econometric approach.

Figure 1.2 demonstrates that the cost composition is different across geographies. While general / ancillary services costs represent the majority of costs (57%) in all hospitals, outpatient costs are a larger percentage of costs in rural (18-19%) vs. urban (12-13%) locations. This is consistent with recent research documenting an increase in outpatient visits among rural hospitals – while also noting the importance of this revenue stream for rural facilities (American Hospital Association, 2019). If EHR functionality is revealed to impact overall operating costs (as hypothesized), the cost sub-components driving that relationship is an interesting follow-up question.

Summary statistics for the independent variables of interest are presented in Table 1.1, which indicates that EHR adoption is high regardless of rural / urban status. This is consistent with recent studies (Everson, Rubin, and Friedman, 2020). The second and third metrics (functionality and use) exhibit more variation, both over time and across rural / urban facilities. Rural hospitals added an average of three EHR functions between 2016 and 2019, while urban facilities reached almost full functionality by 2019. Notably, the “functionality gap” between rural and urban hospitals is reduced over time, moving from a 1.8 additional functions for urban location in 2016 to only 1.1 by 2019. The third measure, EHR use, is higher for urban hospitals but increases only marginally over time, with all hospitals adding only 0.2 uses on average between 2016 and 2018 (the 2019 survey did not include the “use” question).

The values of the control variables differ significantly by rural / urban status (Appendix 1E). In 2019, urban hospitals had over four times as many beds, five times as many employees, and ten times as many total acute days when compared to their rural counterparts. The CMI is also much higher in urban facilities. These rural-urban differences hold in all years of the analysis.

Tables 1.2 to 1.4 summarize the results of our initial regressions. For the full dataset (Table 1.2), none of the EHR metrics are significantly associated with the log of total operating costs at the $\alpha = 0.05$ level. It is important to note that although not statistically significant, the coefficient for

EHR functionality (metric 2) is negative, following the hypothesized direction. Notably, the coefficients for simple adoption and use (metrics 1 and 3) are positive – although again are not statistically significant. The control variables have the expected positive signs, suggesting that the model behaves according to economic theory. In particular, higher case mix indices, more beds, discharges, and total acute days are associated with larger hospital operating costs. These variables measure the size and the scope of a hospital; it is a reasonable finding that larger hospitals have higher costs. The overall fits of the panel regressions are quite good with R^2 values exceeding 0.93.

When the specifications are explored across subsets of rural and urban hospitals, we find that only urban hospitals appear to benefit from significant operating cost decreases associated with increasing EHR functionality (Table 1.4). The respective coefficient suggests that an additional EHR function is associated with total cost reductions of 0.14 percent. Notably, higher levels of EHR *use* are associated with higher costs in urban hospitals, suggesting that new EHR activities lead to additional costs. The control variables demonstrate that the number of employees and total discharges are predictive of costs in urban hospitals, but not rural ones. The overall fit of the models remains strong.

We now turn to the effects of EHR functionality on sub-categories of costs (Tables 1.5 to 1.7). We focus only on the three dominant cost sub-categories (general / ancillary, outpatient, and inpatient), which account for approximately ninety-eight percent of all hospital operating costs (Figure 1.2). Even though we did not find a significant relationship between EHR functionality and total hospital operating costs for the full dataset (at the $\alpha = 0.05$ level), Table 1.5 demonstrates that once we examine the relationship between EHR functionality and each cost sub-category separately, we find a significant and negative relationship between EHR functionality and outpatient costs ($\theta = -0.0016$, $P = 0.019$), for the full dataset. For general / ancillary costs and inpatient costs the estimated coefficients for the control variables are as hypothesized, however, the results do not show a significant relationship with aggregate EHR functionality.

Tables 1.6 and 1.7 extend the sub-category cost analysis to explore rural vs. urban hospitals separately, and indicate that general / ancillary costs and outpatient costs have negative relationships with EHR functionality in urban hospitals (Table 1.7). Outpatient costs demonstrate the largest relationship ($\theta = -0.0022$, $P = 0.036$). The associated coefficient implies that, for urban hospitals, a one-unit increase in EHR functionality is associated with a 0.22 percent decrease in outpatient costs. General / ancillary costs, which were not statistically significant for the full dataset, show a significant negative association with EHR functionality for urban hospitals ($\theta = -0.0014$, $P = 0.034$). For rural hospitals, no cost category shows a significant relationship with EHR functionality (Table 1.6). This result holds when the rural sample is limited to Critical Access Hospitals (CAHs) (not shown).

Lastly, we explore the five sub-categories of EHR functionality to narrow down which EHR functionalities are most directly responsible for the decreasing relationships with the main sub-categories of cost (Tables 1.8 to 1.10). We apply equation (1) using general / ancillary, inpatient, and outpatient costs as our dependent variables, and each of the five sub-categories of EHR functionality as our primary independent variables of interest. We include each sub-category of EHR functionality in separate regressions due to multicollinearity concerns.

The results (Table 1.8) suggest that, for the full dataset, increasing electronic clinical documentation is associated with a significant reduction in general / ancillary costs. The associated coefficient implies cost reduction of 0.44% for each additional electronic clinical documentation function. For inpatient costs, there are no significant reductions associated with any EHR functionality at the $\alpha = 0.05$ level. Outpatient costs demonstrate negative and significant relationships with electronic clinical documentation, and decision support. When all cost categories are aggregated together, only electronic clinical documentation demonstrates a significantly negative relationship ($\theta = -0.0048$, $P < 0.01$; not shown in Table 1.8).

When we extend the analysis to look at rural vs. urban hospitals separately, we find that no EHR functionality is significantly associated with costs reductions in rural hospitals (Table 1.9). Notably, no EHR functionalities are associated with significant costs reductions for outpatient costs in rural areas, which make up a larger proportion of total costs when compared to urban facilities (Figure 1.2). Alternatively, a variety of EHR functionalities are associated with outpatient and general / ancillary costs reductions in urban locations (Table 1.10). For urban hospitals, CPOE ($P = 0.042$) is associated with significant outpatient costs reductions (0.74% for each additional function). In the general / ancillary category, electronic clinical documentation ($\theta = -0.0059$, $P = 0.012$) and results viewing ($\theta = -0.0066$, $P = 0.036$) are associated with significant costs reductions in urban facilities. The trends are similar for aggregate urban operating costs (not shown in Table 1.10), where electronic clinical documentation ($\theta = -0.0047$), results viewing ($\theta = -0.0066$), and CPOE ($\theta = -0.0041$) all demonstrate significantly negative relationships at the $\alpha = 0.05$ level.

6. Discussion

EHRs have become commonplace in U.S. hospitals, but prior research has been unclear about their relationship with operating costs. Rural and urban hospital employees interact with EHRs differently, with fewer resources and expertise available in rural locations. Testing whether the underlying relationships differ across geography can have important implications for future EHR policy. Our results suggest that EHR *functionality*, and not simple adoption, is associated with hospital operating cost reductions in urban areas. This finding is of particular interest because previous studies have largely focused on simple EHR adoption as the metric of interest. The associated coefficient suggest total operating costs savings of 0.14 percent for an average urban hospital for each additional EHR function (Table 1.4). This finding is striking because it suggests a short-term impact: increased EHR functionality in year t is associated with reduced hospital operating costs in that same year. Our finding that EHR *use* is associated with significant cost increases in urban hospitals may be due to the nature of the survey questions asked. We hypothesize that alternative metrics for EHR use, such as those that are part of the Centers for Medicare and Medicaid Services' (CMS) Promoting Interoperability Program (Centers for Medicare and Medicaid Services, 2021), could show different relationships with costs.

While the finding that increasing EHR functionality is associated with lower hospital operating costs is likely of interest to hospital administrators, the results are less optimistic for rural hospitals. EHR functionality is not associated with significant costs decreases at the aggregate level – or for any cost sub-category – among rural hospitals. Therefore, investing in additional total EHR functionality does not appear to be a mechanism to reduce costs for rural hospitals.

In addition, our results show that urban EHR-related cost reductions are driven by both general / ancillary and outpatient costs, but no such relationship is observed for rural hospitals (Table 1.6). This is important because of the higher proportion of costs associated with outpatient services in rural facilities (Figure 1.2). This may be because physician practices that send patients to hospitals for outpatient procedures are more likely to participate in Health Information Exchanges (HIEs) in urban locations, resulting in less time (and cost) spent gathering data at the hospital. An alternative hypothesis is that the lack of a relationship is driven by the fact that rural residents are less likely to manage their personal health information online (Greenberg et al., 2018). Additional research should explore why increased EHR functionality is associated with reduced outpatient costs in urban, but not rural, facilities.

Finally, breaking out EHR functions into sub-categories offers insight into how different EHR capabilities might impact costs across geographies. The results suggest that no EHR functionality sub-category has a significant effect on rural hospitals' operating costs (Table 1.9). In urban hospitals (Table 1.10), the largest impacts to hospital operating costs are seen for CPOE (outpatient costs: $\theta = -00.74$). However, urban hospitals have already invested in nearly all CPOE capabilities (4.96 out of 5 in 2019) and so attempting to reduce costs simply by adding more CPOE functionality is not an option for most facilities. Notably, functionality associated with telehealth (included under other functionality) was not associated with cost reductions for any hospitals; however, the period of analysis was prior to the COVID-19 pandemic when telehealth use soared.

These findings have implications for policy and research discussions. The negative relationship between increased EHR functionality and total hospital operating costs in urban hospitals suggests that the proper way to think of EHR implementation is not in terms of simple adoption, but as a longer-term investment whose payoff is realized as functionality is added. Rural facilities lag behind their urban counterparts in terms of EHR functionality, but policy efforts to improve this functionality should acknowledge the limited potential for short-term cost reductions. The discrepancies across rural – urban locations imply that additional research should attempt to tackle why specific EHR relationships are so much stronger for urban facilities. Specifically, insight into why EHR functionalities reduce *outpatient* costs in urban, but nor rural, hospitals would be particularly useful given the increasing importance of outpatient services for rural facilities.

As an empirical study, our analysis has several limitations. First, we focus on distinct EHR metrics over a particular period; however, there may be better ways to measure EHR use / functionality over time. It is worth noting that we did explore several additional EHR metrics included in the AHA IT Supplement (for example, integration of summary care records received electronically; electronic availability of clinical information) and found no impact on any type of costs for rural or urban hospitals. Second, we are limited by the self-reported nature of the AHA IT Supplement survey data, which may introduce measurement error. Our approach does not explicitly control for the EHR vendor (because it does not vary over time for the vast majority of our hospitals). The AHA IT survey does capture this data for each hospital, and here we see that while the top three vendors (Cerner, Epic, and Meditech) made up eighty-five percent of the urban systems in our sample, they were only chosen by sixty-three percent of rural facilities. Four smaller, alternative vendors (CPSI, Healthland, Evident, and Medhost) captured twenty-two percent of the rural market but only one percent of urban hospitals. The support network offered by the vendor could be important for how the system is rolled out by the hospital and the resulting relationship with workflow / costs.

We also use a dichotomous measure of rurality, and an avenue for future research is to explore whether these results hold across alternative definitions (such as micropolitan vs. non-core counties, or the 9-category rural-urban continuum codes defined by the U.S. Economic Research Service) (Economic Research Service, 2022). Lastly, our two-way fixed effects model controls for time invariant unobserved hospital characteristics; however, there may be time-varying hospital characteristics that are not being captured by our model, such as changes to staff education levels or hospital administration. These unobserved time-varying characteristics could be a potential source of bias. Other potential confounders include baseline outcomes and for-profit status. While our empirical methodology is an improvement on prior cross-sectional studies, an alternative approach is needed in order to make a strict causal argument.

7. Conclusions

Policy discourse on EHRs has moved beyond simple possession of an EHR, with CMS' 2021 Promoting Interoperability Program requiring information on functionalities like e-prescribing and provider-to-patient exchange (Centers for Medicare and Medicaid Services, 2021). Our results demonstrate that specific types of EHR functionality are associated with reduced hospital operating costs in the short term. They also highlight that rurality is an important consideration, as cost reductions are only realized in urban hospitals. A better understanding of why these rural / urban differences exists is crucial, if only because rural hospitals are more likely to operate on thin margins where any cost reduction could prove vital to remaining open. Importantly, urban hospitals are nearing maximum functionality across several EHR sub-categories shown to impact costs, so policies emphasizing the implementation of those specific EHR functions for urban locations may have limited impact. Exploring the impacts of enhanced EHR functionality where adoption is lower (telehealth; remote patient monitoring) is an opportunity for future research, particularly in light of increased demand for these activities due to COVID-19.

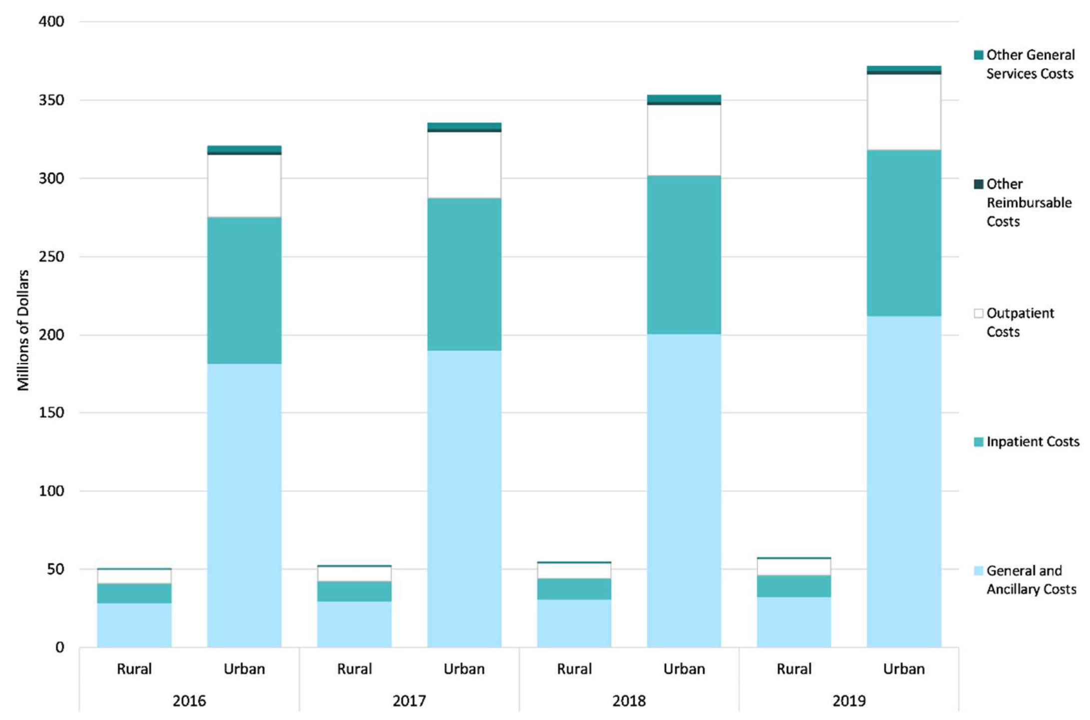

Figure 1.1. Cost breakouts for urban and rural hospitals (in millions of dollars), 2016-2019

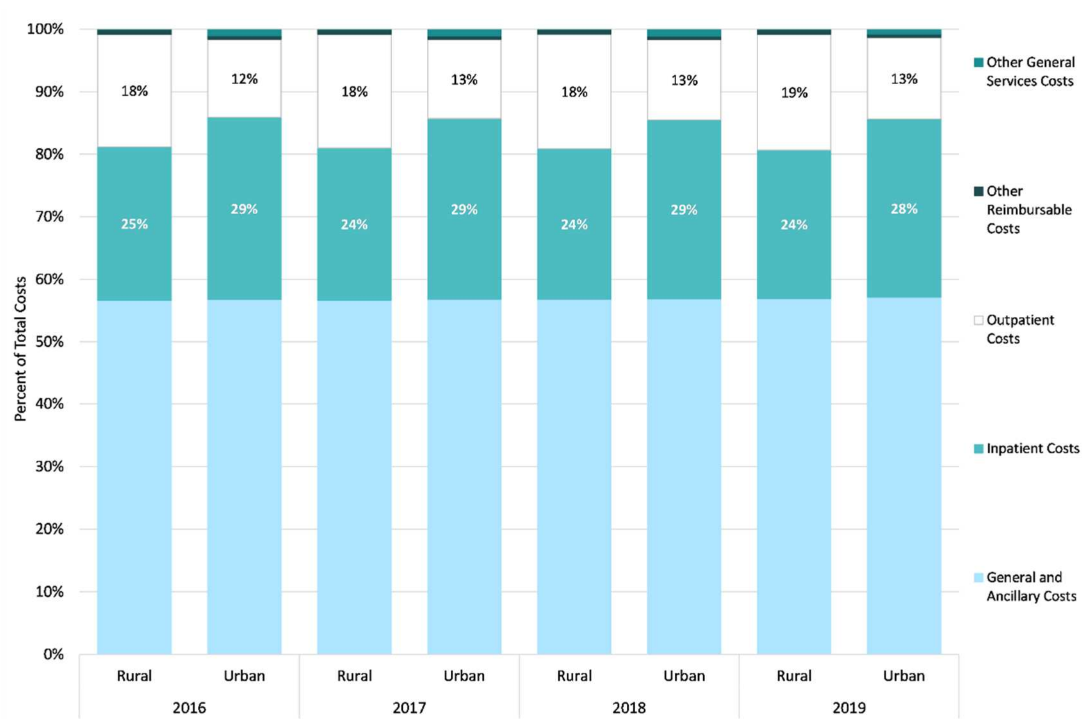

Figure 1.2. Cost composition for urban and rural hospitals (in millions of dollars), 2016-2019

Table 1.1. EHR metrics and t-tests by rural / urban status

		2016			2017		
	Variable	Rural	Urban	Diff.	Rural	Urban	Diff.
1	Simple adoption (certified EHR)	0.98	0.98		0.97	0.98	**
2	All EHR functionalities	21.77	23.57	***	22.23	24.08	***
	Electronic clinical documentation	5.33	5.59	***	5.40	5.74	***
	Results viewing	5.29	5.82	***	5.34	5.88	***
	Computerized provider order entry	4.36	5.55	***	4.48	4.84	***
	Decision support	4.98	5.55	***	5.13	5.61	***
	Other functionalities	1.80	1.87		1.89	2.01	**
3	EHR use	6.38	8.28	***	6.40	8.36	***
	Number of observations	655	941		655	941	

Notes:
[a] EHR = Electronic Health Record.
[b] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[c] American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology Supplement, 2016-2019. The 2019 AHA IT survey did not include the "EHR Use" question.

Table 1.1. EHR metrics and t-tests by rural / urban status cont.

		2018			2019		
	Variable	Rural	Urban	Diff.	Rural	Urban	Diff.
1	Simple adoption (certified EHR)	0.96	0.98	*	0.97	0.98	
2	All EHR functionalities	24.46	25.65	***	24.89	25.97	***
	Electronic clinical documentation	5.78	5.90	***	5.84	5.92	***
	Results viewing	5.66	5.94	***	5.75	5.96	***
	Computerized provider order entry	4.80	4.94	***	4.85	4.96	***
	Decision support	5.52	5.83	***	5.62	5.87	***
	Other functionalities	2.69	3.05	***	2.84	3.24	***
3	EHR use	6.54	8.54	***			
	Number of observations	655	941		655	941	

Notes:
[a] EHR = Electronic Health Record.
[b] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[c] American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology Supplement, 2016-2019. The 2019 AHA IT survey did not include the "EHR Use" question.

Table 1.2. Effects of EHR metrics on total hospital operating costs (full dataset)

DV	log total costs		log total costs		log total costs	
	(1)		(2)		(3)	
EHR metric	Adoption		Functionality		Use	
EHR	0.0057		-0.0009	*	0.0006	
	(0.0096)		(0.0005)		(0.0007)	
Case Mix Index	0.0906	***	0.0900	***	0.1239	***
	(0.0317)		(0.0313)		(0.0432)	
log tot. beds	0.0827	***	0.0822	***	0.0816	***
	(0.0192)		(0.0192)		(0.0242)	
log tot. employees	0.0224		0.0257		0.0111	
	(0.0225)		(0.0224)		(0.0371)	
log tot. discharges	0.0713	**	0.0706	**	0.0434	
	(0.0330)		(0.0330)		(0.0302)	
log tot. acute days	0.0766	***	0.0769	***	0.1106	***
	(0.0285)		(0.0285)		(0.0262)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.9362		0.9358		0.9351	
Number Observations	6,336		6,336		4,749	

Notes:
[a] EHR = Electronic Health Record.
[b] EHR Metric refers to (1) EHR Adoption, (2) EHR Functionality, and (3) EHR Use in subsequent columns.
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[g] The American Hospital Association's (AHA) Information Technology Supplement did not include the variable used in this study to measure EHR Use (number of products) in 2019; thus the number of observations in model (3) are lower.

Table 1.3. Effects of EHR metrics on total hospital operating costs (rural hospitals)

DV	log total costs		log total costs		log total costs	
	(1)		(2)		(3)	
EHR metric	Adoption		Functionality		Use	
EHR	0.0057		-0.0005		-0.0002	
	(0.0106)		(0.0006)		(0.0011)	
Case Mix Index	0.1257	***	0.1254	***	0.1364	*
	(0.0443)		(0.0439)		(0.0739)	
log tot. beds	0.0872	***	0.0868	***	0.0872	**
	(0.0298)		(0.0297)		(0.0379)	
log tot. employees	0.0085		0.0088		-0.0100	
	(0.0197)		(0.0196)		(0.0363)	
log tot. discharges	0.0298		0.0289		0.0252	
	(0.0407)		(0.0404)		(0.0477)	
log tot. acute days	0.0819	**	0.0830	**	0.1056	***
	(0.0330)		(0.0327)		(0.0357)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.8423		0.8415		0.8329	
Number Observations	2,604		2,604		1,952	

Notes:
[a] EHR = Electronic Health Record.
[b] EHR Metric refers to (1) EHR Adoption, (2) EHR Functionality, and (3) EHR Use in subsequent columns.
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[g] The American Hospital Association's (AHA) Information Technology Supplement did not include the variable used in this study to measure EHR Use (number of products) in 2019; thus the number of observations in model (3) are lower.

Table 1.4. Effects of EHR metrics on total hospital operating costs (urban hospitals)

DV	log total costs		log total costs		log total costs	
	(1)		(2)		(3)	
EHR metric	Adoption		Functionality		Use	
EHR	0.0113		-0.0014	**	0.0019	***
	(0.0145)		(0.0006)		(0.0006)	
Case Mix Index	0.0641	*	0.0637	*	0.1192	***
	(0.0375)		(0.0376)		(0.0271)	
log tot. beds	0.0528	***	0.0529	***	0.0549	***
	(0.0180)		(0.0179)		(0.0193)	
log tot. employees	0.1312	***	0.1301	***	0.0830	***
	(0.0228)		(0.0228)		(0.0185)	
log tot. discharges	0.1302	***	0.1306	***	0.0640	***
	(0.0392)		(0.0402)		(0.0217)	
log tot. acute days	0.0922	**	0.0897	**	0.1426	***
	(0.0446)		(0.0454)		(0.0307)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.9202		0.9198		0.9161	
Number Observations	3,732		3,732		2,797	

Notes:
[a] EHR = Electronic Health Record.
[b] EHR Metric refers to (1) EHR Adoption, (2) EHR Functionality, and (3) EHR Use in subsequent columns.
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[g] The American Hospital Association's (AHA) Information Technology Supplement did not include the variable used in this study to measure EHR Use (number of products) in 2019; thus the number of observations in model (3) are lower.

Table 1.5. Effects of EHR functionality on cost sub-categories (full dataset)

DV	log general / ancillary costs		log inpatient costs		log outpatient costs	
EHR Functionality	-0.0005		-0.0009		-0.0016	**
	(0.0006)		(0.0007)		(0.0007)	
Case Mix Index	0.1176	***	0.0180		0.1018	**
	(0.0372)		(0.0515)		(0.0443)	
log tot. beds	0.0531	**	0.1380	***	0.0814	***
	(0.0248)		(0.0299)		(0.0316)	
log tot. employees	0.0377	*	0.0057		0.0382	
	(0.0195)		(0.0264)		(0.0278)	
log tot. discharges	0.0741	*	0.0816	**	0.0719	
	(0.0385)		(0.0404)		(0.0500)	
log tot. acute days	0.0802	**	0.1674	***	-0.0207	
	(0.0330)		(0.0419)		(0.0423)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.9348		0.9287		0.7587	
Number Observations	6,336		6,336		6,336	

Notes:
[a] EHR = Electronic Health Record.
[b] Unit of observation is hospital-year.
[c] Sample includes annual data from 2016 to 2019.
[d] Robust standard errors, clustered by hospital, in parenthesis.
[e] $* \ P < 0.10, ** \ P < 0.05, *** \ P < 0.01$.

Table 1.6. Effects of EHR functionality on cost sub-categories (rural hospitals)

DV	log general & ancillary costs		log inpatient costs		log outpatient costs	
EHR Functionality	0.0001		-0.0007		-0.0012	
	(0.0008)		(0.0008)		(0.0008)	
Case Mix Index	0.1420	***	0.0143		0.1239	**
	(0.0503)		(0.0693)		(0.0623)	
log tot. beds	0.0557		0.1383	***	0.0843	*
	(0.0372)		(0.0447)		(0.0478)	
log tot. employees	0.0232		-0.0134		0.0153	
	(0.0192)		(0.0216)		(0.0218)	
log tot. discharges	0.0246		0.0522		-0.0112	
	(0.0443)		(0.0517)		(0.0598)	
log tot. acute days	0.0981	***	0.1463	***	0.0415	
	(0.0355)		(0.0543)		(0.0460)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.8463		0.8230		0.4982	
Number Observations	2,604		2,604		2,604	

Notes:
[a] EHR = Electronic Health Record.
[b] Unit of observation is hospital-year.
[c] Sample includes annual data from 2016 to 2019.
[d] Robust standard errors, clustered by hospital, in parenthesis.
[e] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 1.7. Effects of EHR functionality on cost sub-categories (urban hospitals)

DV	log general & ancillary costs		log inpatient costs		log outpatient costs	
EHR Functionality	-0.0014	**	-0.0005		-0.0022	**
	(0.0006)		(0.0008)		(0.0011)	
Case Mix Index	0.1039	**	0.0527		0.0827	
	(0.0510)		(0.0535)		(0.0531)	
log tot. beds	0.0299		0.1045	***	0.0661	**
	(0.0218)		(0.0211)		(0.0265)	
log tot. employees	0.1244	***	0.1106	***	0.2015	***
	(0.0249)		(0.0237)		(0.0360)	
log tot. discharges	0.1432	***	0.1406	***	0.1698	***
	(0.0536)		(0.0505)		(0.0604)	
log tot. acute days	0.0743		0.2377	***	-0.1213	*
	(0.0553)		(0.0612)		(0.0624)	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.9073		0.9133		0.7362	
Number Observations	3,732		3,732		3,732	

Notes:
[a] EHR = Electronic Health Record.
[b] Unit of observation is hospital-year.
[c] Sample includes annual data from 2016 to 2019.
[d] Robust standard errors, clustered by hospital, in parenthesis.
[e] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 1.8. Effects of EHR functionality sub-categories on general/ancillary, inpatient, and outpatient costs (full dataset)

DV	log ancillary costs		log inpatient costs		log outpatient costs	
Electronic clinical documentation	-0.0044	**	-0.0043	*	-0.0057	**
	(0.0019)		(0.0025)		(0.0025)	
Results viewing	-0.0003		-0.0022		-0.0027	
	(0.0027)		(0.0025)		(0.0025)	
Computerized provider order entry	-0.0012		-0.0035	*	-0.0042	*
	(0.0021)		(0.0021)		(0.0025)	
Decision support	-0.0001		-0.0008		-0.0050	**
	(0.0017)		(0.0019)		(0.0022)	
Other functionalities	-0.0004		-0.0007		-0.0023	
	(0.0018)		(0.0019)		(0.0024)	
Other controls	Yes		Yes		Yes	
Hospital Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Overall R^2	0.9349		0.9289		0.8081	
Number Observations	6,336		6,336		6,336	

Notes:
[a] EHR = Electronic Health Record.
[b] EHR functionalities introduced individually (i.e. five separate regressions for each DV).
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 1.9. Effects of EHR functionality sub-categories on general/ancillary, inpatient, and outpatient costs (rural hospitals)

DV	log ancillary costs	log inpatient costs	log outpatient costs
Electronic clinical documentation	-0.0028	-0.0047	-0.0043
	(0.0024)	(0.0032)	(0.0031)
Results viewing	0.0008	-0.0025	-0.0021
	(0.0031)	(0.0029)	(0.0028)
Computerized provider order entry	0.0001	-0.0025	-0.0021
	(0.0027)	(0.0027)	(0.0031)
Decision support	0.0011	-0.0004	-0.0044
	(0.0023)	(0.0024)	(0.0029)
Other functionalities	0.0006	0.0003	-0.0024
	(0.0026)	(0.0029)	(0.0034)
Other Controls	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Overall R^2	0.8465	0.8236	0.5015
Number Observations	2,604	2,604	2,604

Notes:
[a] EHR = Electronic Health Record.
[b] EHR functionalities introduced individually (i.e. five separate regressions for each DV).
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 1.10. Effects of EHR functionality sub-categories on general/ancillary, inpatient, and outpatient costs (urban hospitals)

DV	log ancillary costs		log inpatient costs	log outpatient costs	
Electronic clinical documentation	-0.0059	**	0.0003	-0.0069	*
	(0.0023)		(0.0030)	(0.0041)	
Results viewing	-0.0066	**	-0.0012	-0.0080	*
	(0.0032)		(0.0037)	(0.0042)	
Computerized provider order entry	-0.0029		-0.0044	-0.0074	**
	(0.0021)		(0.0027)	(0.0036)	
Decision support	-0.0021		-0.0004	-0.0057	*
	(0.0022)		(0.0027)	(0.0029)	
Other functionalities	-0.0012		-0.0011	-0.0009	
	(0.0019)		(0.0020)	(0.0032)	
Other Controls	Yes		Yes	Yes	
Hospital Fixed Effects	Yes		Yes	Yes	
Year Fixed Effects	Yes		Yes	Yes	
Overall R^2	0.9077		0.9133	0.7374	
Number Observations	3,732		3,732	3,732	

Notes:
[a] EHR = Electronic Health Record.
[b] EHR functionalities introduced individually (i.e. five separate regressions for each DV).
[c] Unit of observation is hospital-year.
[d] Sample includes annual data from 2016 to 2019.
[e] Robust standard errors, clustered by hospital, in parenthesis.
[f] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

CHAPTER II

COMMUNITY SOCIODEMOGRAPHICS AND RURAL HOSPITAL SURVIVAL

Abstract

This study uses a national sample of 985 rural hospitals at risk of financial distress to analyze the relationship between community sociodemographic characteristics and hospital survival or closure. We control for financial distress using the Financial Distress Index (FDI) developed by the Sheps Center for Health Services Research. Community characteristics are retrieved from the Census and the Robert Wood Johnson Foundation. First, we use t-tests to measure whether sociodemographic variables' yearly means differ between rural communities with hospitals at risk of financial distress that closed between 2010 and 2019, and those that remained open. Then, we use multilevel Weibull proportional hazards regressions to uncover which sociodemographic factors are significantly associated with survival (at the $\alpha = 0.05$ level). Our initial results confirm that closures of rural hospitals at risk of financial distress disproportionately affect communities with higher percentages of Black population, lower incomes, higher child poverty, higher unemployment, and higher percentage of adults reporting fair or poor health, higher obesity levels, and higher rates of smoking. However, most of the characteristics are not associated with higher rates of closure in the multivariate analysis. The final results suggest that rural hospitals at risk of financial distress are more likely to experience closure if their

communities have higher rates of unemployment (Hazard ratio $= 1.36$, $P < 0.05$) and uninsured residents under 65 (Hazard ratio $= 1.13$, $P < 0.05$).

Keywords: rural hospitals, hospital closure, financial distress, sociodemographic characteristics.

1. Introduction

Rural hospital closures are a source of concern to rural health policymakers and providers, especially since areas with the highest number of rural hospital closures tend to be some of the country's most vulnerable ones (The Chartis Center for Rural Health, 2020). Rural residents not only have higher risk of facing adverse health conditions (Hartley, 2004; Monnat and Pickett, 2011; Blackwell, Lucas, and Clarke, 2014; Centers for Disease Control and Prevention, 2017; Economic Research Service, 2018; Economic Research Service, 2020), but they also face more barriers to access health care (Weeks, 2018). Closure of rural hospitals only exacerbates these problems. The evidence is clear that rural hospital closures lead to additional losses, such as local physicians (Germack, Kandrack, and Martsolf, 2019) and other industries like laundry services, retail services, and construction (Brooks and Whitacre, 2011). These losses spill over to the broader economy: closure of the only hospital in a rural community reduces per-capita income by four percent and increases the unemployment rate by 1.6 percentage points (Holmes et al., 2006).

Hospitals at risk of financial distress are at a particularly high risk of closure. The University of North Carolina Sheps Center for Health Services Research developed the Financial Distress Index (FDI) to forecast the risk of distress in two years (Holmes, Kaufman, and Pink, 2017). Based on the FDI score, hospitals are assigned high, mid-high, mid-low, or low risk levels (Table 2.1 shows the predictors included in the FDI – nearly all of which are characteristics of the hospital, and not the surrounding community) (Holmes, Kaufman, and Pink, 2017). It has been shown that the FDI risk levels successfully differentiate rural hospitals facing an increasing risk of closure (Holmes, Kaufman, and Pink, 2017). However, not all rural hospitals identified by the FDI as being at risk of financial distress have closed. In fact, only seven percent of the rural hospitals considered at high and mid-high of financial distress between 2010 and 2019 experienced closure. This suggests that beyond rurality and risk of financial distress, there may be other factors influencing hospital closure. We hypothesize that within the pool of rural hospitals at risk of financial distress, community sociodemographic characteristics could be associated with closure events.

Most studies on hospital closures focus on the association between intrinsic hospital characteristics, particularly financial characteristics, and hospital closure. Some of the most common factors associated with rural hospital closures include poor financial health, aging facilities, low occupancy rates, and difficulty recruiting and retaining health care professionals (Singh, 2008; Liu et al., 2011). Some studies go beyond the association between hospital-specific factors and hospital closures, and attempt to account for hospital community characteristics. The community characteristics that are most commonly captured by these studies are population density, income, poverty level, and age. An important limitation of these studies is that relevant sociodemographic characteristics, such as race, ethnicity, or unemployment rates are often left out of the analysis (Lillie-Blanton et al., 1992; Williams, Hadley, and Pettengill, 1992; Kaufman et al. 2016).

Several prior studies document the association between community characteristics and hospital closure, accounting for sociodemographic characteristics such as race and ethnicity. However, most of these studies focus on urban hospital closure. These urban-focused studies have shown that loss of health services is more likely to occur in areas with larger percentages of racial and ethnic minorities (Sager, 1983; Hsia, Kellermann, and Shen, 2011; Ko et al., 2014). Only a few analyses specifically account for sociodemographic characteristics of the population in the geographic areas surrounding a rural hospital – and most are quite dated (Mayer et al., 1987; Mullner et al., 1989; Hospitals, 1990). None of these efforts focus solely on hospitals that are at financial risk.

To our knowledge, the most recent paper that examines the possible associations between sociodemographic characteristics of rural communities and hospital closure is the paper written by Thomas, Holmes, and Pink (2016), who fitted a multilevel logit regression model on a cross-sectional dataset to examine the differences in the communities of rural hospitals that closed between January 2005 and December 2015, and those that remained open in the same period, controlling for financial distress. The authors found that while closed rural hospitals were located in markets with higher rates of unemployment and more non-Caucasian residents, these factors were not statistically significant in predicting closure rates (Thomas, Holmes, and Pink, 2016).

Our study builds on the aforementioned effort by Thomas, Holmes, and Pink (2016) and adds to the literature on hospital closure in three different ways. First, we analyze the relationship between community sociodemographic characteristics and rural hospital closure. This differs from the vast majority of the literature, which focuses on hospitals' intrinsic characteristics. Second, we focus exclusively on rural hospitals at risk of financial distress, which the literature suggests are at a particularly high risk of closure. Finally, we use survival analysis to measure the associations between community sociodemographic characteristics and rural hospital survival or closure. To our knowledge, there is no other study on rural hospital closure in the United States that uses survival analysis with data from more than a single state.

Survival analysis is also called time-to-event analysis. The point of these studies is to follow subjects over time and observe at which point in time they experience the event of interest (UCLA Advanced Research Computing, 2021). Originally, survival analysis was used only to study mortality and morbidity in biomedical sciences. At present, the concept of survival analysis no longer simply refers to a biomedical event; survival data are now collected and analyzed in social science, engineering, political science, business management, and economics (Liu, 2012). In survival analysis we are interested in how long subjects stay in the sample (survival), and their risk of experiencing the event of interest (hazard rates) (Sullivan, 2020). Survival analysis post-estimation tools can be useful for visualizing how specific factors impact the probability of survival over time.

A survival process describes a time period from a specified starting point to the occurrence of an event of interest. Therefore, the primary feature of survival data is the description of a change in status. This feature of a change in status makes survival analysis similar to more traditional binary statistical approaches, such as the logistic model. Traditional statistical models, however, ignore the timing of occurrence of the event of interest, and, therefore, miss the ability to describe a time-to-event process (Liu, 2012). Testing and visualizing relationships in the years leading up to the event is an important part of survival models that can provide relevant insight for policymakers.

2. Objectives

The objective of this study is to determine whether hospital community sociodemographic characteristics are associated with the survival or closure of rural hospitals at risk of financial distress between 2010 and 2019. This study builds on the work of Thomas, Holmes, and Pink (2016), who explored which community characteristics were associated with rural hospital closures, while controlling for financial distress (using the FDI). Our hypothesis is that this analysis could be extended by taking a different methodological approach and expanding their sample to include more recent data. Survival models, unlike logistic models, allow us to account for the time of occurrence of the event of interest, and, therefore, have the ability to describe a time-to-event process. Plotting survival functions for specific community characteristics enhances the discussion of rural hospital closure.

3. Data

Data on hospital characteristics are retrieved from the American Hospital Association (AHA) Annual Survey of hospitals. We include in our dataset only hospitals classified as "general and surgical," removing specialty hospitals. The initial product of our data aggregation is a panel dataset consisting of 2,472 hospitals from 2010 to 2019. A hospital community is defined as the county where a hospital is located, and is considered rural if the county has a Rural-Urban Continuum Code (RUCC) greater than or equal to four (Economic Research Service, 2020). Table 2.2 shows that 115 hospitals closed between 2010 and 2019, about seventy-six percent of the hospitals that closed were located in rural areas. It also shows that roughly half of all hospitals in our dataset (both rural and urban) are at high or mid-high risk of financial distress.

Data on hospital closure and risk of financial distress are provided by the Sheps Center for Health Services Research. A hospital is considered closed if "it has stopped providing general, short-term, acute impatient care. A hospital is not considered closed if it: merged with, or was sold to, another hospital but it continued to provide inpatient care; converted to critical access status; or both closed and reopened during the same year and the same location" (The Sheps Center for Health Services Research, 2014). For the purposes of this study, a hospital is considered at risk of financial distress if it is assigned a high or mid-high risk level based on its FDI at any point between 2010 and 2019 (Holmes, Kaufman, and Pink, 2017). Eighty percent of the rural hospitals that closed between 2010 and 2019 were at risk of financial distress.

We restrict our final dataset to rural hospitals at risk of financial distress, since both rurality and risk of financial distress are associated with an increased risk of closure. Our final dataset consists of 985 rural hospitals from 2010 to 2019 (9,850 hospital-year observations). About seven percent of these rural hospitals at risk of financial distress experienced closure between 2010 and 2019.

We hypothesize that local community sociodemographic characteristics are associated with the survival or closure of these hospitals. The county-level sociodemographic variables included in this study are: population, median age, median family income, percent of children in poverty, percent of the population sixty-five and older, percent unemployed, percent of the population under sixty-five without health insurance, percent less than a High School graduate, percent with a Bachelor's degree or higher, percent White, percent Black, percent Hispanic / Latino, percent reporting fair or poor health, percent reporting obesity, and percent reporting smoking. Appendix 2A describes each of the sociodemographic variables included in this study and their sources. All data are gathered annually.

4. Methods

In the first stage of our analysis, we measure whether community sociodemographic characteristics differ between rural hospitals at risk of financial distress that closed between 2010 and 2019, and those that remained open during the same time-period. To do this, we first estimate yearly means for each variable; then, using t-tests, we measure whether they are significantly different for the two groups at the $\alpha = 0.05$ level. Significant differences in yearly sociodemographic variables' means between the two groups could be an indication that the sociodemographic composition of rural hospitals at risk of financial distress that close is different from the sociodemographic composition of those that remain open. This will be important for assessing who is impacted by such closures; however, they tell us little about risks over time.

The second stage of our study is the survival analysis. First, we perform univariate survival analyses to explore whether each sociodemographic variable is statistically associated with time-to-event (hospital closure). Then, we fit a final survival model including only the statistically significant variables in our univariate analyses (at the $\alpha = 0.05$ level). We use this stepwise elimination scheme because we hypothesize that all sociodemographic variables could be potentially associated with the survival or closure of rural hospitals – but rely on the multivariate model to isolate the most important factors.

For our survival analysis, we use multilevel Weibull proportional hazards models with hospital and state random effects to account for time-invariant unobserved factors at the hospital and state levels. This means that our model is a proportional hazards model, conditional on the random effects. In other words, conditional on the random effects, the observations from the same group are assumed to be independent. Random effects are assumed to be independent and identically distributed. The groups (hospitals / states) are also assumed to be independent and identically distributed. We assume that, conditional on the covariates, the censoring distribution is independent of the time-to-event distribution and the random effects (STATA, 2021).

Beyond fitting a model and obtaining its parameters estimates, it is important to test the model's fit and assumptions. First, we test the 'proportional hazards' assumption (that the hazards are proportional over time) by testing the distribution of the standardized covariate residuals. Second, we test whether the baseline hazard functional form is appropriate (i.e. Weibull distribution vs. exponential, log-normal, log-logistic, or gamma distribution) by running our parametric survival analysis model under different specifications and using the Akaike's Information Criterion (AIC) and the Bayesian Information Criteria (BIC) to compare competing parametric models. Finally, we test whether a multilevel model is the correct specification for our data, using a likelihood ratio test comparing the fit of a Weibull proportional hazards model and a multilevel Weibull proportional hazards model with hospital and state random effects.

5. Results

Table 2.3 displays the sociodemographic variables yearly means for rural hospitals at risk of financial distress that closed between 2010 and 2019 and those that remained open during that same timeframe. The results suggest that most variables' *means* are significantly different between the two groups, for the years covered by the analysis. On average, rural communities with hospitals at risk of financial distress that experienced closure had lower median family income, higher percentages of child poverty, higher unemployment, lower percentages of White population, higher percentages of Black population, higher percentages of fair or poor health days reported, higher obesity rates, and higher rates of smoking.

Survival outcomes are modeled as a nonlinear function of the explanatory variables, therefore, model coefficients are not always directly interpretable. In most situations, a hazard ratio is used to simplify the interpretation. This is analogous to an odds ratio in the setting if multiple logistic regression analysis (Sullivan, 2020). In a multilevel proportional hazards survival model, these hazard ratios should be interpreted as ‘conditional hazard ratios’, that is, conditional on the random effects (STATA, 2021). If the hazard ratio for a predictor is not statistically different from one, then that predictor does not affect survival. If the hazard ratio is less than one, then the predictor is protective (i.e. an increase in the variable is associated with an increase in the time the hospital remains open). If the hazard ratio is greater than one, then the predictor is associated with increased risk (i.e. an increase in the covariate is associated with an increased risk of closure) (Sullivan, 2020).

Table 2.4 shows the results from the univariate survival analyses. These results suggest that many variables are significantly associated with the survival of rural hospitals at risk of financial distress, and are potential candidates for our final model. It is important to mention, however, that our univariate analyses are likely to be influenced by confounding factors that can significantly impact the association between the variables under examination (Liu, 2012). Some sociodemographic variables may be related to hospital survival when considered alone (univariate analyses), but not after adjustment for other sociodemographic factors.

The results in table 2.4 show that median family income and percent White have hazard ratios significantly lower than one, suggesting a protective relationship. Alternatively, the percent of children in poverty, percent unemployed, percent under sixty-five without health insurance, percent less than a High School graduate, percent Black, percent reporting fair or poor health, and percent reporting smoking are each associated with increased risk of closure, when considered individually. Population, median age, percent sixty-five and older, percent with a Bachelor's degree or higher, percent Hispanic, and percent obese, are not significant predictors of rural hospital closure, and, therefore, are not candidates for our final model.

Table 2.5 shows our final survival model that includes only the sociodemographic variables that had a p-value less than 0.05 in the univariate analyses. Only three variables remain significant predictors of rural hospital closure in the multivariate survival model: percent of the population unemployed, percentage under sixty-five without health insurance, and percentage reporting smoking. The associated hazard ratios imply that, with all other variables held constant, a one percentage point increase in unemployment raises the hazard rate (i.e. probability of rural hospital closure) by 36.12 percent. Further, as the percentage of the population under sixty-five without health insurance increases by one percentage point, the hazard rate increases by 13.46 percent. The results also suggest that as the percentage of adult smokers increase by one percentage point, the hazard rate increases by 11 percent. Appendix 2B shows that these results hold when the model controls for the actual value of the FDI. It is important to note that, as expected, a higher FDI is associated with a significant increase in the risk of closure (hazard ratio of 1.42).

An important reason for using survival analysis is the ability to estimate and visualize survival and hazard functions. The survival function, $S(t)$, reports the probability of surviving beyond time t; while the hazard function, $h(t)$, reports the probability that the event of interest occurs in a given time t, conditional on the subject having survived to that point. The hazard rate can go from zero (meaning no risk) to infinity (meaning the certainty of experiencing the event at that instant) (Cleves, Gould, and Yulia, 2008). Our post-estimation analysis focuses on unemployment rates and rates of uninsurance for the population under age sixty-five.

Figures 2.1 and 2.2 show survival functions for rural hospitals at risk of financial distress from 2010 to 2019. Figure 2.1 shows survival functions for different levels of community unemployment, while Figure 2.2 assesses survival functions for different levels of population under sixty-five without health insurance. Note that all functions equal one in 2010, and decrease as we approach the end of our study in 2019. The survival function at the mean value of all covariates, for instance, decreases to the mean survival rate of 0.93 in 2019. However, the rate of the decrease varies significantly depending on the level of community unemployment and population under sixty-five without health insurance. Hospitals in our sample that have higher rates of community unemployment and population under sixty-five without health insurance experience sharper decreases in their survival functions. This means that, on average, the probability of remaining open is dramatically lower for financially distressed rural hospitals in communities with higher levels of unemployment and uninsurance.

Figures 2.3 and 2.4 show the corresponding hazard functions for the hospitals in our sample. All functions equal zero at the beginning of our study in 2010 and increase as we approach the end of our study in 2019. Here too, the rate of increase differs depending on the level of unemployment and population under sixty-five without health insurance. The sharp increases in the hazard functions suggest that, on average, the probability of experiencing closure is higher for rural hospitals in communities with higher rates of unemployment and uninsurance.

Finally, regarding model assumptions and goodness-of-fit, first, we test the proportionality assumption. After producing both covariate-specific and global tests of the proportional hazard assumptions, we conclude that there is no evidence that the proportional hazards assumption is violated ($P > 0.05$ for all our sociodemographic variables). Second, we test if the Weibull distribution is a good fit for our baseline hazard. After running our model under exponential, log-logistic, and log-normal hazard functional forms and obtaining AIC and BIC metrics to compare between competing parametric models, we conclude that the Weibull distribution is the appropriate distribution for our baseline hazard (Weibull AIC: 800.70, BIC: 878.31 / Exponential AIC: 942.04, BIC: 1019.4 / Log-logistic AIC: 801.87, BIC: 886.29 / Log-normal AIC: 820.01, BIC: 904.43). Finally, a likelihood ratio test (multilevel Weibull vs. Weibull model) suggests that the multilevel model is appropriate for our data ($P = 0.06$).

6. Discussion

This study examines the associations between community sociodemographic characteristics and the survival of rural hospitals at risk of financial distress. Our results suggest that community sociodemographic composition differs significantly between hospitals that closed between 2010 and 2019 and those that remained open. Communities with hospitals that experienced closure had, on average, lower incomes, higher child poverty, higher unemployment, a lower percentage of their population White, a higher percentage of their population Black, a higher percentage of adults reporting fair or poor health, higher obesity levels, and higher rates of smoking. These findings are similar to other recent studies (Sager, 1983; Hsia, Kellermann, and Shen, 2011; Ko et al., 2014; Kaufman et al., 2016; Thomas, Holmes, and Pink, 2016).

Most importantly, our multivariate survival analysis suggests that, as hypothesized, certain community sociodemographic characteristics are associated with the closure of rural hospitals at risk of financial distress between 2010 and 2019. Notably, however, many of the characteristics just discussed – race / poverty / obesity / income – were *not* statistically linked to risk of closure. Alternatively, higher rates of community unemployment, population under sixty-five without health insurance, and adult smokers were associated with increased risks of rural hospital closure (at the $\alpha = 0.05$ level). The estimated hazard ratios suggest that a one percentage point increase in community-level unemployment rate is associated with a thirty-six percentage point increase in the likelihood of hospital closure; similarly, a one percentage point increase in under sixty-five uninsurance rates is associated with a thirteen percentage point increase in the likelihood of closure. This finding for the uninsured population is particularly noteworthy given the similar uninsurance rates across communities with open /closed hospitals in Table 2.3.

Health care facilities are subject to economic forces, and ultimately these economic forces are what determine whether they can remain open or not. We hypothesize that increases in hospitals' community unemployment and uninsurance levels lead to increased spending on uncompensated care, which in turn weakens hospitals' financial positions. As hospitals' financial positions weaken, their likelihood of closure increases. Both unemployment and lack of health insurance are sociodemographic factors that influence the affordability of health care (Kearney et al., 2021) – but these are not explicitly controlled for in metrics like the FDI. Most of the time, when unemployed or uninsured individuals use care and cannot pay for it themselves, the cost of that care is uncompensated (Karpman, Coughlin, and Garfield, 2021). If a large share of a hospital's care is uncompensated, such care becomes a burden on the hospital's finances, especially for rural hospitals who tend to have lower operating margins (Holmes, Pink, and Friedman, 2013).

This study has important implications for policy and research. In terms of health equity, our results agree with previous research finding that the closure of rural hospitals at risk of financial distress may disproportionately affect vulnerable sectors of the population and racial minorities (Sager, 1983; Hsia, Kellermann, and Shen, 2011; Ko et al., 2014; Kaufman et al., 2016; Thomas, Holmes, and Pink, 2016). However, when we move beyond simple t-tests into survival analysis, we find that many of these factors (race, income) are not associated with risk of closure. Our survival analysis results suggest that the risk of rural hospital closure increases as the levels of community unemployment and uninsurance rise. Recent studies have also found that increases in community unemployment (Thomas, Pink, and Reiter, 2019; Chatterjee, Lin, and Venkataramani, 2022; Planey et al., 2022) and uninsurance (Lindrooth et al., 2018; Duggan, Gupta, and Jackson, 2019) are associated with hospitals' financial distress and closure, but have stopped short of documenting the time-relevant associations of these variables. These considerations are important when assessing policies that can help at-risk hospitals and communities.

Our results also have implications for Medicaid expansion. Several studies have found that states that expand their Medicaid programs experience large reductions in uninsurance rates (Griffith, Evans, and Bor, 2017; Hayes et al., 2017; Hudson and Moriya, 2017; Long et al., 2017; McMorrow et al., 2017; Choi, Lee, and Matejkowski, 2018). Policies like Medicaid expansion, which promote improved health insurance coverage for previously uninsured people, help reduce uncompensated care expenditures and strengthen hospitals' financial positions (Schubel and Broaddus, 2016; Sojourner and Golberstein, 2017). Previous studies have also found that Medicaid expansion is associated with improved hospital financial performance and lower likelihoods of closure (Lindrooth et al., 2018; Duggan, Gupta, and Jackson, 2019). Our analysis reinforces those results while demonstrating the compounding nature of the time component.

We note that data availability on local levels of unemployment and uninsurance varies greatly. The Bureau of Labor Statistics (BLS) produces county-level data on employment through the Local Area Unemployment Statistics (LAUS); these estimates are typically available with only a two-three month delay. Uninsurance rates, however, come with much longer lag times. The Census' Small Area Health Insurance Estimates (which is used by the Robert Wood Johnson Foundation) typically reports county-level data with a roughly 18-month lag (2019 data was reported in June 2021). This makes following local trends in uninsurance rates much more challenging than for unemployment.

Our findings also demonstrate that local sociodemographic factors are not only associated with health *outcomes*, but also with health care *access* in rural communities. There is already growing evidence of the association between sociodemographic factors and negative health outcomes (LaPar et al., 2011; Kleindorfer et al., 2012; Pudrovska and Anikputa, 2012; Bikdeli et al., 2014; Hampras et al., 2014; Kroch et al., 2016; Campione, Smith, and Mardon, 2017; Soden et al., 2018; Delaney, Essien, and Navathe, 2021). Hospital closures lead to reduced access to health care, which in turn leads to increased risk of poor health outcomes and health disparities (McCarthy et al., 2021). If sociodemographic factors are associated not only with health outcomes, but also with hospital closure and, therefore, with health care *access*, there is a more complex relationship between sociodemographic factors and health outcomes that acknowledged. Negative reciprocal relationships between sociodemographic factors, hospital closure, health care access, and health outcomes could create complex health disparities.

The results here support the hypothesis that community sociodemographic factors are associated with the survival or closure of rural hospitals at risk of financial distress. It is important to acknowledge, however, that isolating the association between a particular sociodemographic factor and hospital closure is problematic because sociodemographic factors are often deeply intertwined. For instance, unemployed adults are more likely to be non-Hispanic Black, to have less than a high school education, and to have family income below the poverty level. Further, overall, more unemployed adults report fair or poor health compared to employed adults (Driscoll and Bernstein, 2012). At the same time, there is evidence of disparities in health insurance coverage for vulnerable populations in the U.S., including people of color (James et al., 2007).

Our study has important limitations. First, although time-invariant unobserved variables are accounted for in our multilevel model, time-variant unobserved variables are not. These difficult-to-measure variables, such as community leadership or levels of community engagement could potentially bias the results. Second, because we are using a multilevel model, hazard ratios are conditional on the group random effects. Third, survival analysis is subject to the usual cautions about causal inference with observational data. Differences in survival or closure cannot be attributed to sociodemographic factors because there is no experimental factor assignment. Finally, the stepwise regression model approach used in this analysis, in which the entry of variables to a final model is based on statistical criteria, is controversial as data driven strategies may not generalize beyond the sample chosen. However, our sample is national in scope, which may reduce some of this concern.

7. Conclusions

Despite a growing amount of data, our understanding of why some rural hospitals at risk of financial distress experience closure and some do not remains limited. We use survival analysis to shed light on this issue. The results show that rural hospitals at risk of financial distress are more likely to experience closure if their communities have higher unemployment rates and higher percentages of their population uninsured. Informed communities and hospitals should make their local and federal representatives aware of these linkages, and should follow the associated data-points to the extent possible. Policymakers, in turn, should recognize these relationships and note that broader policies seeking to impact unemployment and uninsurance rates are also important for local health infrastructure viability.

Issues of sociodemographic disparities and health equity are complex. Further research needs to address the relationships between community sociodemographic characteristics, hospital closure, health care access and health outcomes in rural communities. Hospital closures are taking place in rural areas with particularly vulnerable populations. Decreased access to health care caused by rural hospital closure will likely result in a worsening of health outcomes to already vulnerable sectors of the population. Reducing inequities in health access and outcomes requires policy initiatives that address how sociodemographic variables factor into them.

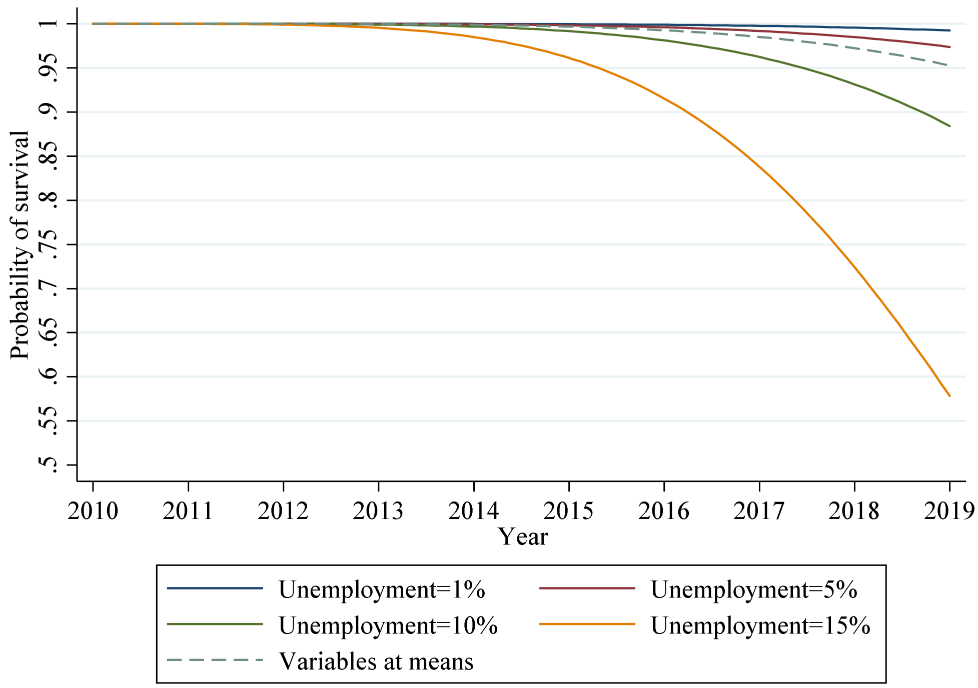

Figure 2.1. Survival functions for rural hospitals at risk of financial distress (2010-2019) with different community unemployment levels

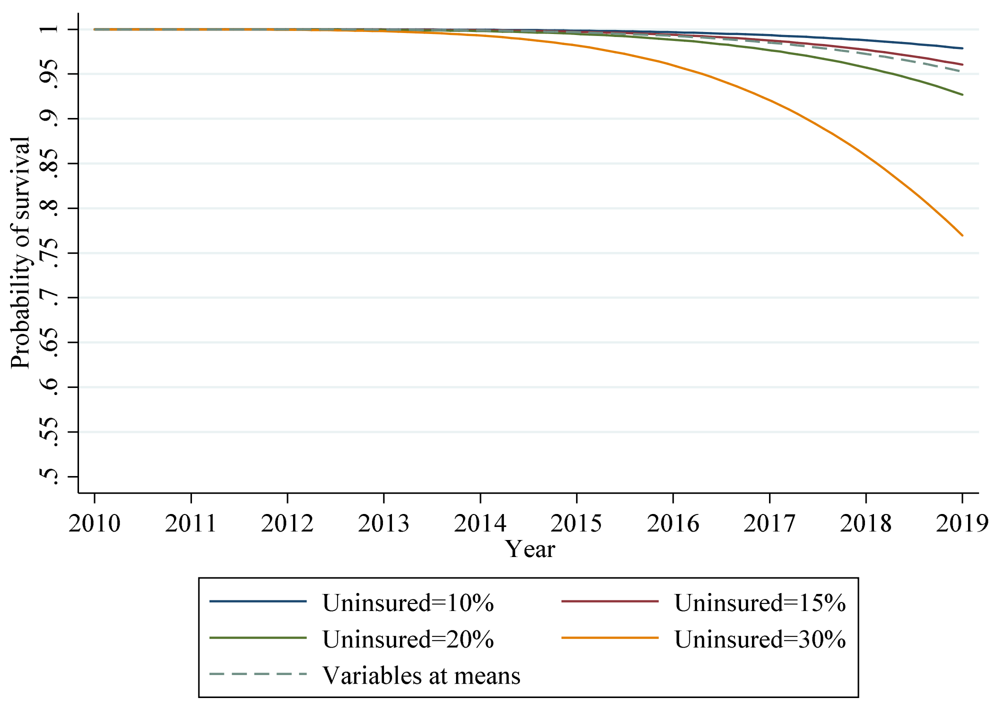

Figure 2.2. Survival functions for rural hospitals at risk of financial distress (2010-2019) with different percentages of their population under 65 without health insurance

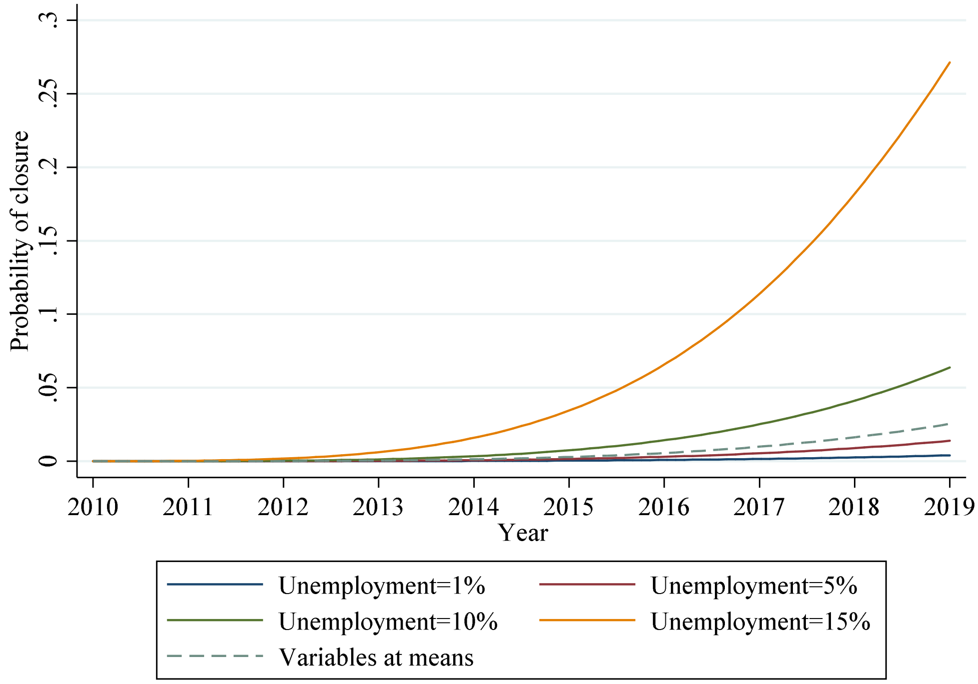

Figure 2.3. Hazard functions for rural hospitals at risk of financial distress (2010-2019) with different community unemployment levels

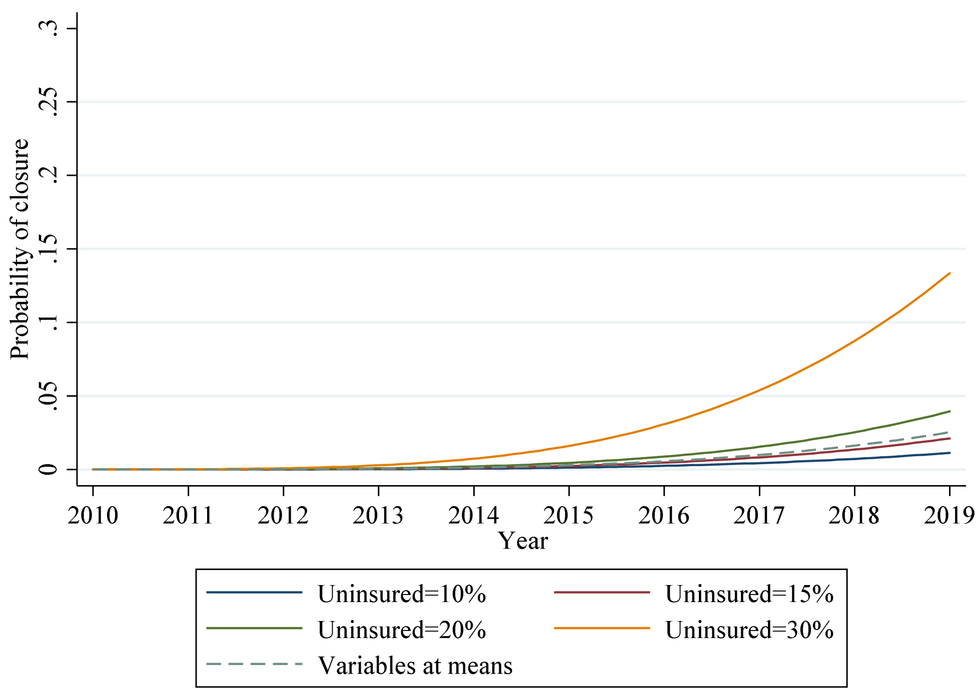

Figure 2.4. Hazard functions for rural hospitals at risk of financial distress (2010-2019) with different percentages of their population under 65 without health insurance

Table 2.1. Financial Distress Index (FDI) model predictors

	Predictors
Financial performance	Percent total margin Retained earnings Percent benchmarks met
Government reimbursement	CAH status Medicare to Medicaid fee index
Organizational characteristics	For-Profit status Net patient revenue
Market characteristics	Miles to nearest hospital (>100 beds) Market share Proportion households in poverty Market population

Source: Holmes, G., Kaufman, B., & Pink, G. (2017). Predicting Financial Distress and Closure in Rural Hospitals. The Journal of Rural Health, 33(3), 239–249.

Table 2.2. Summary statistics – hospital closure and risk of financial distress by rural / urban status (2010-2019)

	Rural	Urban	Total
Number of hospitals in our dataset	2,004	468	2,472
Number of hospitals at risk of financial distress	985	244	1,229
Number of hospitals not at risk of financial distress	1,019	224	1,243
Number of closed hospitals	87	28	115
Number of open hospitals	1,917	440	2,357
Number of closed hospitals at risk of financial distress	70	22	92
Number of closed hospitals not at risk of financial distress	17	6	23
Number of open hospitals at risk of financial distress	939	230	1,169
Number of open hospitals not at risk of financial distress	978	210	1,189
Percentage of hospitals in our dataset rural vs. urban	81.07%	18.93%	100%
Percentage of hospitals at risk of financial distress	49.15%	52.14%	49.72%
Percentage of closed hospitals rural vs. urban	75.65%	24.35%	100.00%
Percentage of closed hospitals at risk of financial distress	80.49%	78.57%	80.00%

Table 2.3. Sociodemographic variables yearly means for rural counties with hospitals at risk of financial distress that experienced closure vs. rural counties with hospitals at risk of financial distress that did not (2010 – 2019)

	Population		Median age		% Elderly		MFI		% Child Poverty	
	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Open	Closed
2010	26.74	32.71	40.73	40.19	16.78	16.63	47.55[a]	44.95[a]	24.99[a]	27.68[a]
2011	26.79	32.76	40.95	40.45	16.98	16.78	48.88[a]	46.02[a]	25.21[a]	27.90[a]
2012	26.82	32.77	41.13	40.69	17.23	16.94	49.37[a]	46.04[a]	27.98[a]	31.32[a]
2013	26.81	32.74	41.29	40.95	17.52	17.29	49.77[a]	46.24[a]	28.42[a]	32.29[a]
2014	26.80	32.68	41.42	41.19	17.83	17.65	50.71[a]	47.14[a]	28.32[a]	31.98[a]
2015	26.76	32.59	41.57	41.40	18.04	17.97	51.23[a]	47.28[a]	28.43[a]	32.22[a]
2016	26.72	32.51	41.68	41.63	18.59	18.53	52.58[a]	48.34[a]	27.11[a]	30.88[a]
2017	26.66	32.42	41.80	41.71	18.94	18.89	54.35[a]	50.41[a]	26.97[a]	30.68[a]
2018	26.62	32.37	41.91	41.82	19.34	19.26	56.23[a]	52.57[a]	26.26[a]	29.75[a]
2019	26.58	32.31	42.04	41.98	19.74	19.66	58.27[a]	54.50[a]	25.53[a]	28.68[a]

Notes:
[a] Yearly mean differences statistically significant ($P < 0.05$).

Table 2.3. Sociodemographic variables yearly means for rural counties with hospitals at risk of financial distress that experienced closure vs. rural counties with hospitals at risk of financial distress that did not (2010 – 2019) cont.

	% Unemployed		% Uninsured		% Less HS		% BA or more		% White	
	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Open	Closed
2010	6.15[a]	6.93[a]	18.90	17.70	8.30	7.76	83.02[a]	77.55[a]	8.18	8.82
2011	9.45[a]	10.78[a]	21.21	20.43	8.38	7.82	83.10[a]	77.76[a]	8.00	8.72
2012	9.59[a]	10.74[a]	20.17	20.23	8.39[a]	7.75[a]	83.16[a]	77.68[a]	7.85	8.64
2013	9.00[a]	10.27[a]	20.14	19.97	8.43[a]	7.80[a]	83.06[a]	77.41[a]	7.66[a]	8.59[a]
2014	8.04[a]	9.18[a]	19.57	19.74	8.48	7.93	82.96[a]	77.32[a]	7.49[a]	8.42[a]
2015	7.68[a]	8.68[a]	19.05	19.46	8.50[a]	7.83[a]	82.81[a]	77.16[a]	7.33[a]	8.22[a]
2016	6.68[a]	7.64[a]	18.97	19.14	8.52[a]	7.84[a]	82.63[a]	76.93[a]	7.23[a]	8.00[a]
2017	5.98[a]	6.83[a]	15.81	16.77	8.61	8.03	82.51[a]	76.65[a]	7.11	7.79
2018	5.75[a]	6.35[a]	13.38	14.38	8.64	8.18	82.39[a]	76.37[a]	6.96	7.56
2019	4.96[a]	5.46[a]	12.39	13.63[a]	8.71	8.27	82.28[a]	76.24[a]	6.81	7.43

Notes:
[a] Yearly mean differences statistically significant ($P < 0.05$).

Table 2.3. Sociodemographic variables yearly means for rural counties with hospitals at risk of financial distress that experienced closure vs. rural counties with hospitals at risk of financial distress that did not (2010 – 2019) cont.

	% Black		% Hispanic		% Fair/poor health		% Obese		% Smokers	
	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Open	Closed
2010	9.96[a]	16.92[a]	7.76	5.05	19.20[a]	21.51[a]	29.33[a]	30.50[a]	23.57[a]	25.49[a]
2011	9.99[a]	16.76[a]	8.01	5.48	19.12[a]	21.04[a]	30.04[a]	31.57[a]	23.05[a]	24.77[a]
2012	9.98[a]	16.78[a]	8.33	5.73	18.97[a]	20.97[a]	31.69[a]	33.16[a]	22.50	23.41
2013	9.96[a]	16.75[a]	8.53	5.99	18.73[a]	21.07[a]	31.69[a]	33.16[a]	21.76	22.67
2014	9.97[a]	16.70[a]	8.69	6.23	19.59[a]	22.57[a]	31.96[a]	33.35[a]	22.89	23.60
2015	10.00[a]	16.67[a]	8.87	6.47	19.59[a]	22.57[a]	32.18[a]	33.33[a]	22.89	23.60
2016	10.00[a]	16.65[a]	9.03	6.58	18.67[a]	20.71[a]	32.48[a]	33.48[a]	19.33[a]	20.68[a]
2017	10.00[a]	16.62[a]	9.19	6.68	18.77[a]	20.59[a]	32.46	33.36	18.91[a]	20.44[a]
2018	10.04[a]	16.77[a]	9.32	6.74	19.17[a]	21.10[a]	32.89	33.55	18.81[a]	20.69[a]
2019	10.04[a]	16.83[a]	9.45	6.78	19.17[a]	21.10[a]	33.49	34.02	18.81[a]	20.69[a]

Notes:
[a] Yearly mean differences statistically significant ($P < 0.05$).

Table 2.4. Univariate analyses – Multilevel Weibull proportional hazards regressions results

	Fixed effects		Random effects	
Time to closure	Coefficient	Hazard ratio	State	Hospital
Population (thousands)	0.0048	1.0048	0.2972	1.11E-33
	(0.0042)	(0.0042)		
Median age	-0.0177	0.9825	0.2908	8.55E-35
	(0.0268)	(0.0263)		
Percent elderly	0.0525	0.9488	0.2835	3.57E-34
	(0.0341)	(0.0324)		
Median family income (thousands USD)	-0.0698[a]	0.9326[a]	0.2559	1.59E-33
	(0.0148)	(0.0138)		
Percent child poverty	0.0494[a]	1.0506[a]	0.2451	1.89E-34
	(0.0142)	(0.0149)		
Percent unemployed	0.3334[a]	1.3957[a]	0.4906	2.86E-34
	(0.0446)	(0.0623)		
Percent uninsured	0.1190[a]	1.1264[a]	0.3811	1.81E-33
	(0.0283)	(0.0319)		
Percent less than High School	0.0837[a]	1.0873[a]	0.2305	8.22E-34
	(0.0393)	(0.0428)		
Percent Bachelor's degree or more	-0.0708	0.9316	0.2432	8.23E-36
	(0.0539)	(0.0502)		
Percent White	-0.0138[a]	0.9863[a]	0.2794	4.58E-18
	(0.0065)	(0.0064)		
Percent Black	0.0185[a]	1.0187[a]	0.2694	1.02E-35
	(0.0067)	(0.0006)		
Percent Latino or Hispanic	-0.0253	0.9750	0.3266	2.90E-35
	(0.0147)	(0.0143)		
Percent fair or poor health	0.0831[a]	1.0867[a]	0.1813	6.35E-34
	(0.0251)	(0.0272)		
Percent obese	0.0400	1.0408	0.2914	1.11E-33
	(0.0327)	(0.0341)		
Percent smokers	0.1319[a]	1.1410[a]	0.1766	3.63E-33
	(0.0243)	(0.0277)		
Number of observations	9850			
Number of state groups	45			
Number of hospital groups	985			

Notes:
[a] Coefficients and hazard ratios statistically significant ($P < 0.05$).
[b] Standard errors in parenthesis.

Table 2.5. Final model – Multilevel Weibull proportional hazards regression results

Time to closure	Coefficient	Hazard ratio
Fixed effects		
Median family income (thousands USD)	-0.0371	0.9635
	(0.0285)	(0.0274)
Percent child poverty	-0.0661	0.9360
	(0.0344)	(0.0322)
Percent unemployed	0.3084[a]	1.3612[a]
	(0.0584)	(0.0795)
Percent uninsured	0.1263[a]	1.1346[a]
	(0.0342)	(0.0388)
Percent less than High School	-0.1302	0.8692
	(0.0633)	(0.0551)
Percent White	0.0259	1.0263
	(0.0156)	(0.0160)
Percent Black	0.0290	1.0294
	(0.0164)	(0.0169)
Percent fair or poor health	-0.0036	0.9964
	(0.0434)	(0.0432)
Percent smokers	0.1044[a]	1.1101[a]
	(0.0341)	(0.0379)
Random effects		
State	0.2191	
Hospital	6.62E-34	
P-value	0.0627	
Number of observations	9850	
No. groups state	45	
No. groups hospital	985	
P-value	0.000	

Notes:
[a] Coefficients and hazard ratios statistically significant ($P < 0.05$).
[b] Standard errors in parenthesis.

CHAPTER III

TELEHEALTH AND REMOTE PATIENT MONITORING: DID EARLY ADOPTION OF TELECOMMUNICATION TECHNOLOGIES HELP RURAL AND URBAN HOSPITALS AVOID REVENUE DECLINE DURING COVID-19?

Abstract

The objective of this study is to determine whether implementing telehealth and remote patient monitoring before the onset of the COVID-19 pandemic (2019) allowed hospitals to avoid significant drops in revenue during the pandemic (2020), and to determine whether the results differ for rural and urban hospitals. We match national-level data on telehealth and remote patient monitoring implementation in 2019 from the American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology (IT) Supplement, with revenue data in 2019 and 2020 from the American Hospital Directory (AHD). We then perform linear regressions on a cross-sectional dataset of 1,997 U.S. hospitals. Our dependent variables are the inpatient revenue, outpatient revenue, gross patient revenue and net patient revenue percentage changes from 2019 to 2020. The adoption of telehealth and remote patient monitoring in 2019 (before the COVID-19 emergency declaration) serve as the primary variables of interest. We control for changes in hospital characteristics (such as number of employees and discharges) from 2019 to 2020. Our

results suggest that implementing telehealth – but not remote patient monitoring – before the onset of the COVID-19 pandemic (in 2019) allowed hospitals to avoid significant drops in revenue during the pandemic (from 2019 to 2020).

Keywords: telehealth, remote patient monitoring, hospital revenue, COVID-19, rural hospitals, urban hospitals.

1. Introduction

The rapid development of telecommunications and the pressure to develop more efficient health care models resulted in the development of telehealth. Telehealth is a term that arose over forty years ago and is defined by the U.S. Department of Health and Human Services as "the use of electronic information and telecommunication technologies to support and promote long distance clinical health care, patient and professional health-related education, public health and health administration" (U.S. Department of Health and Human Services, 2021). Telehealth is an umbrella term that covers a vast range of tools and technologies used to deliver health care at a distance (Chang et al., 2021). Proponents of telehealth have argued that it has the potential to improve health care access and coordination, increase efficiency, reduce 'no show' rates, decrease waiting times, increase patient volume, decrease non-urgent cases from urgent care, improve patient experience and convenience, and decrease costs for both practices and patients (Almallah and Doyle, 2020; Cabrera, et al., 2021; Rangachari, Mushiana, and Herbert, 2021). Previous research indicates that telehealth can reduce workload (Downes et al., 2017) and increase both patient and provider satisfaction (Thiyagarajan et al., 2020). Telehealth has also been shown to increase engagement between health care providers and patients (Kruse et al., 2017).

Despite the reduction in the digital divide in the late 2000s and despite evidence supporting telehealth as a potential solution to improve health care access and delivery, prior to the COVID-19 pandemic, the use of telehealth was mostly limited to a few medical specialties (Rangachari, Mushiana, and Herbert, 2021). By 2019, physicians reported to be optimistic about improvements to practice efficiency due to telehealth, but telehealth adoption was growing at a modest rate (Bosworth et al., 2020). Several studies argue that the slow uptake of telehealth before the COVID-19 pandemic was caused by both patient- and provider- related barriers. A literature review performed by Standing et al. (2018) suggests that barriers to telehealth were persistent and remained unchanged, at least over the period covered by their analysis, from 2000 to 2015.

According to the literature, the most prevalent practice-related barriers were: concerns about the impact of the staff-patient relationship, lack of trust in technology, concerns about the quality of care, staff discomfort, lack of universal coverage, uncertainty around reimbursements, lack of uniform licensure between states, and cost of implementing telehealth innovations (Standing et al., 2018; Talebian, 2020; Chang et al., 2021; Malliaras et al., 2021; Rangachari, Mushiana, and Herbert, 2021). While the most prevailing patient-related barriers were: lack of access to required resources, limited digital literacy, patient discomfort, language barriers, and lack of trust in receiving appropriate care via telehealth (Cottrell and Russell, 2020; Turolla et al., 2020; Chang et al., 2021). However, patients appeared less reluctant than health professionals to engage in telehealth (Standing et al., 2018).

On January 31, 2020 the U.S. Department of Health and Human Services (DHHS) declared a public health emergency in response to COVID-19. The COVID-19 pandemic entailed social distancing mandates and the prioritization of health care resources. As a result, virtually all in-person outpatient visits and elective procedures were cancelled in many parts of the county, and many practices suffered a significant drop in volume (Cohen et al., 2020). From the beginning of the outbreak, telehealth was sought as a potential way to maintain critical access to care while keeping both patient and providers safe from exposure to the COVID-19. On March 24, 2020, the Centers for Medicare and Medicaid Services (CMS) declared that the use of telehealth was vital to combat COVID-19. Around that time, the CMS and the DHHS also encouraged private insurers to make available and increase usage of telehealth services.

The public health emergency declaration was followed by comprehensive changes to telehealth policies by the Federal Government, the DHHS, the CMS, private insurers, and state legislators that aimed to broaden telehealth access. These measures included reimbursing telehealth visits at the same rate as in-person visits, relaxing privacy regulations, expanding services that can be delivered through telehealth, allowing the use of technologies that do not comply with Health Insurance Portability and Accountability Act requirements, and lifting geographic and originating-site restrictions (Centers for Medicare and Medicaid Services, 2020; U.S. Department of Health and Human Services, 2020; Weigel et al., 2020). These changes to telehealth policies removed some of the largest barriers that had limited telehealth adoption prior to the COVID-19 pandemic and rapidly expanded and encouraged telehealth use (Meyer et al., 2020).

The rapid changes in regulation around telehealth and the removal of regulatory barriers led to greater acceptance and implementation of telehealth. The United Hospital Fund reported that, in March 2020, telehealth claims in the United States were 4,347% higher than in March 2019 (Gelburd, 2020). A similar report by McKinsey and Company found that while eleven percent of U.S. consumers had used a telehealth service in 2019, forty-six percent had done it by May 2020 (Cohen et al., 2020). In the same lines, an issue brief published in July 2020 by the Health and Human Services Assistant Secretary for Planning and Evaluation reported that about forty-four percent of Medicare primary care visits were provided via telehealth in April compared to less than one percent before the COVID-19 public emergency was declared. What is most important, telehealth may be here to stay. According to the Kaiser Family Foundation, “telemedicine, what was once a niche model of health care delivery, is now breaking into the mainstream in response to the COVID-19 crisis” (Weigel et al., 2020).

The COVID-19 emergency had important implications for revenue generation by hospitals and practices. In 2020, primary care practices faced a projected fifteen billion USD revenue loss due to COVID-19 (Basu et al., 2020). According to a survey by the Healthcare Financial Management Association, nine out of ten health care executives surveyed predicted that their organization’s revenues would be significantly lower in 2020, compared to pre-COVID-19 levels. Telehealth was expected not only to provide access to health care during the public health emergency, but also to mitigate some of the revenue losses during the COVID-19 pandemic. Nonetheless, not all hospitals and practices had implemented telehealth prior to the COVID-19 pandemic. We hypothesize that hospitals that implemented telehealth before the COVID-19 emergency declaration were able to respond in a timelier manner to the health emergency and, therefore, experienced smaller decreases in revenue during the pandemic, compared to the hospitals and practices that had not implemented telehealth services prior to the COVID-19 pandemic.

Before the COVID-19 pandemic there was already evidence supporting that telehealth could potentially become a tool for hospitals and practices to decrease costs and increase revenues. The advent of COVID-19 and the subsequent exponential increase in telehealth use has created a newfound interest in the impact of telehealth on hospital and practice finances. This subject is important as there is evidence that both patients and health care providers are interested in continuing to use telehealth post COVID-19 (Almallah and Doyle, 2020). If telehealth is here to stay, it is critical to have a better understanding of how telehealth can impact hospital finances, in particular revenue and sustainability.

Although literature on telehealth has grown over the years to be a substantial body of work, there have been difficulties in extracting value from telehealth activities. After performing an extensive literature review from 2000 to 2015, Standing et al. (2018) concluded that there is a need for a research agenda on telehealth that provides clear evidence of its financial benefits. There are previous studies that examine how telehealth implementation and use impacted hospital revenue during the COVID-19 pandemic. However, most of these studies are simulations (Barrington et al., 2021) or focus on a particular medical specialty (Svider et al., 2020; Cabrera et al., 2021). To our knowledge, this is the first study to use U.S. hospital-level observational data to measure how telehealth implementation prior to the COVID-19 emergency declaration influenced hospital revenue changes during the pandemic.

2. Objectives

This study examines the relationship between telehealth / remote patient monitoring implementation before the COVID-19 emergency declaration (2019), and revenue changes during the COVID-19 pandemic (from 2019 to 2020). We perform simple linear regressions where our dependent variables are the gross patient revenue, inpatient revenue, outpatient revenue, and net patient revenue percentage changes (from 2019 to 2020), and our main independent variables of interest are telehealth and remote patient monitoring implementation before the COVID-19 emergency declaration (in 2019). We hypothesize that hospitals that adopted telehealth and remote patient monitoring before the COVID-19 pandemic were able to respond in a timelier manner to the health emergency and suffered less severe revenue losses due to the COVID-19 pandemic, than those who did not. We run separate regressions for hospitals in rural vs. urban locations to determine whether rural status influences the relationship between telehealth / remote patient monitoring implementation (prior to COVID-19) and revenue changes during the pandemic.

3. Data

We match national hospital-level data on telehealth and remote patient monitoring implementation in 2019 from the American Hospital Association's (AHA) Annual Survey of Hospitals Information Technology (IT) Supplement, with revenue data (2019 and 2020) from the American Hospital Directory (AHD). The product of our data aggregation is a cross-sectional dataset of 1,997 hospitals. AHA Annual Survey of Hospitals IT Supplement data have been used before to document telehealth adoption and use by academic researchers (Adler-Milstein, Kvedar, and Bates, 2014; Hong et al., 2020). AHD is a private company that provides data from hospitals nationwide, using public and private sources. AHD data have also been used in recent academic research (Pratt, 2008; Cooley, 2020).

The two independent variables of interest (telehealth and remote patient monitoring implementation in 2019) are retrieved from the following questions in the AHA Annual Survey of Hospitals IT Supplement (2019): "Does your hospital currently have a computerized system which allows for: Other Functionalities: Telehealth?", and "Does your hospital currently have a computerized system which allows for: Other functionalities: Remote patient monitoring?" These questions measure whether hospitals have Electronic Health Record (EHR) systems with advanced software functionality that build their own telehealth and remote patient monitoring platforms directly into their EHR. For instance, large EHR providers such as EPIC and Cerner support telehealth and remote patient monitoring capabilities such as patient messaging, uploading images and documents, symptom checkers for patients to self-triage, home monitoring devices (such as blood pressure monitors), video visits, multiparty conferences, screen sharing, amongst others.

Gross patient revenue, inpatient revenue, outpatient revenue, and net patient revenue data in 2019 and 2020 are retrieved from the American Hospital Directory (AHD). The AHD obtains these data from the most recent Medicare Cost Report Worksheet G-2, Parts I and II – Statement of Patient Revenues and Operating Expenses. This worksheet requires the reporting of total patient revenues and operating expenses for the entire facility. Inpatient revenue data are retrieved from Part I, Line 17 and include revenues generated by the hospital component of the complex, swing-bed Skill Nurse Facility (SNF), swing-bed Nursing Facility (NF), intensive care unit, coronary care unit, burn intensive care unit, surgical intensive care unit, and revenue generated from other long-term care sub-providers. Outpatient revenue data are retrieved from Part I, Lines 19 to 26 and include outpatient services, Rural Health Clinic, Federally Qualified Health Center, Home Health Agency, ambulance services, outpatient rehabilitation providers, ambulatory surgical centers, and hospice revenue. Gross patient revenue data are retrieved from Part I, Line 28, which sums Lines 1 through 27. Finally, net patient revenue data are retrieved from Part II, Line 2. Net patient revenue data is calculated by subtracting all revenues not received from gross patient revenue. Revenues not received include provision for bad debts, contractual adjustments, charity discounts, teaching allowances, policy discounts, administrative adjustments, implicit price concessions, and other deductions from revenue (American Hospital Directory, 2018).

The variables used as controls are changes in the number of beds, employees, discharges, and acute days from 2019 to 2020, general hospital status, and Case Mix Index (CMI) in 2020. Control variables are retrieved from the American Hospital Directory (AHD). The AHD obtains the number of beds, employees, discharges and acute days from the most recent Medicare Cost Report Worksheet S-3, Part I – Hospital and Hospital Health Care Complex Statistical Data. The number of general beds are retrieved from Line 7, Column 2. The number of employees are retrieved from Line 14, Column 10. The number of inpatient discharges are retrieved from Line 14, Column 15. The number of acute days are retrieved from Line 14, Column 8. Finally, AHD obtains the Case Mix Index (CMI) by averaging the Medicare Severity Diagnosis – Related

Groups (MS-DGRs) weight for all of a hospital's Medicare volume. The CMI indicates the relative severity of a patient population.

Table 3.1 displays the summary statistics for telehealth and remote patient monitoring implementation by rural / urban status. A hospital is considered rural if it is in a county with a Rural-Urban Continuum Code (RUCC) greater than or equal to four (Economic Research Service, 2020). About thirty-four percent of the hospitals in our dataset are rural. Ninety-four percent of rural and ninety-six percent of urban hospitals in our dataset report data on telehealth implementation. With seventy-five percent rural and seventy-four percent urban hospitals having telehealth implemented in 2019. A smaller proportion of both rural and urban hospitals report data on remote patient monitoring implementation (89% rural and 94% urban). Only fifty percent rural and fifty-three percent urban hospitals reported having remote patient monitoring implemented in 2019. As we can see in Table 3.3, neither telehealth nor remote patient monitoring implementation was significantly different between rural and urban hospitals in 2019 (at the $\alpha = 0.05$ level).

The number and proportion of hospitals that had revenue decreases during the COVID-19 pandemic (from 2019 to 2020) are displayed in Table 3.2. Almost half of the hospitals in our dataset report gross patient revenue, inpatient revenue, and outpatient revenue decreases in 2020. It is important to note, however, that a significantly higher proportion of rural hospitals experienced revenue decreases, compared to their urban counterparts (gross patient: 59% rural vs. 44% urban / inpatient: 61% rural vs. 41% urban / outpatient: 55% rural vs. 47% urban). The proportion of hospitals experiencing net patient revenue decreases in 2020 was even greater, with almost sixty percent of the hospitals in our dataset reporting losses.

Table 3.4 shows summary statistics for the hospital characteristics by rural / urban status. As expected, CMI, the number of beds, employees, discharges, and acute days are significantly larger for urban hospitals than for rural hospitals. The differences in size and scope between rural and urban hospitals have been discussed before in the literature, with rural hospitals being significantly smaller than urban hospitals (Hatten and Connerton, 1986). When it comes to type of facility, a greater proportion of rural hospitals are general hospitals (97%), compared to their urban counterparts (75%). As we can see in Table 3.4, both rural and urban hospitals experienced decreases in the number of beds, employees, discharges, and acute days during the pandemic. However, it is important to note that rural hospitals experienced significantly larger decreases, compared to their urban counterparts. For instance, acute day losses and total employees decreases were twice as large for rural hospitals as for urban hospitals (-8% vs. -4%, and -2% vs. -1%, respectively).

4. Methods

We use linear regression models to examine the relationship between telehealth / remote patient monitoring implementation before the COVID-19 emergency declaration (in 2019) and revenue changes during the COVID-19 pandemic (from 2019 to 2020). Our dependent variables are revenue percentage changes (gross patient / inpatient / outpatient / net patient) from 2019 to 2020, and telehealth / remote patient monitoring implementation (in 2019) serve as the primary independent variables of interest. To control for alternative effects on revenue changes caused by hospital-specific characteristics, we include variables measuring hospital characteristics in our regressions, such as CMI, type of hospital, and changes in number of beds, discharges, employees, and acute days, from 2019 to 2020. We run separate regressions for hospitals in rural vs. urban locations to determine whether rural status influences the relationship between telehealth / remote patient monitoring implementation (prior to COVID-19) and revenue changes during the COVID-19 pandemic.

We hypothesize that the estimated coefficients for our independent variables of interest (telehealth / remote patient monitoring implementation in 2019) are positive and statistically significant for all our regression models. Meaning, we expect that early implementation of telehealth and remote patient monitoring prior to the COVID-19 emergency declaration is associated with non-negative changes in revenue during the COVID-19 pandemic (from 2019 to 2020). Our identification relies on the assumption that changes in hospital revenues not caused by telehealth / remote patient monitoring implementation are captured by the control variables in our model.

Beyond fitting a regression model, it is important to test that the data meet the multivariable simple linear regression assumptions to make sure that the estimated coefficients are not misleading. For our study, we test for homogeneity of the variance (homoskedasticity), normality of the residuals, linearity and multicollinearity. To test for homoskedasticity, we use Breusch-Pagan tests (at the $\alpha = 0.05$ level). To test for normality, we use Kernel density plots, inter-quartile-ranges and plots of standardized normal probabilities. To test for linearity, we use augmented partial residual plots with each of our explanatory variables. Finally, to test for multicollinearity we use Variance Inflation Factors (VIF) with a tolerance of 0.1.

5. Results

We start our analysis with data diagnostics to see how well our data meets the multivariable linear regression assumptions. First, we test for homogeneity of variance of the residuals using Breusch-Pagan tests. For the regressions with percentage changes in gross patient, inpatient, and outpatient revenue as dependent variables, we reject the null hypothesis and conclude that there is significant evidence that heteroskedasticity is present. The presence of heteroskedasticity was expected given the differences in hospital size and scope between smaller / rural hospitals and larger / urban hospitals. To guard against the presence of heteroskedasticity we use robust standard errors in the aforementioned regression models. Using robust standard errors helps us avoid incorrect hypothesis tests in the presence of heteroskedasticity. However, it does not address the other implication of heteroskedasticity, that the least square estimator is not the minimum variance estimator (Hill, Griffiths, and Lim, 2018). We believe that despite the least square estimator no longer being best in the presence of heteroskedasticity, we can still get valid estimates given the size of our sample.

We move on to our tests for normality of the residuals using Kernel density plots, inter-quartile-ranges, and plots of standardized normal probabilities. Using inter-quartile ranges, we reject the presence of any severe outliers and find that the distribution of the residuals seems symmetric, suggesting that the residuals for each of our fitted models have an approximately normal distribution. We find no indication of severe deviations from normality on the Kernel-density plots, and the plots of standardized normal probabilities. Therefore, we conclude that the residuals from our fitted models are close to a normal distribution.

We test for linearity using augmented partial residual plots with each of our explanatory variables. The residual plots are fairly uniform for CMI and the percentage changes in the number of employees, discharges, and acute days. The residual plot for the percentage change in number of beds is less uniform but it does not suggest that we have concerning non-linearities in the data. Finally, we test for multicollinearity using Variance Inflation Factors (VIF) with a tolerance of 0.1; tolerance defined as 1/VIF value. Our variables have VIF values that suggest multicollinearity is not a problem in our models.

Once model assumptions are tested, we proceed with our analysis. We start by examining how hospital characteristics (our control variables) impact revenue changes (Tables 3.5 to 3.8). First, we note that a higher CMI, as well as increases in number of employees and discharges are associated with increases in all revenue categories, as expected. A higher CMI indicates that a hospital treats a greater number of complex, resource-intensive patients; and procedures that are more complex typically generate more revenue. The relationship between higher a CMI and higher revenues has been established before (Lee, Melnick, and Myrtle, 2005). Increases in the number of acute days, on the other hand, are associated with significant increases in gross patient, inpatient, and net patient revenue increases, but are not associated with any significant changes in outpatient costs. It is a reasonable finding that changes in patient length of stay significantly affect inpatient revenues, but not outpatient revenues.

We have confirmed that the model behaves according to economic theory and our control variables have the expected signs. Now, we move on to the analysis of our independent variables of interest (Tables 3.5 to 3.8). As hypothesized, telehealth implementation prior to the COVID-19 emergency declaration is associated with significant increases in gross patient, inpatient, outpatient and net patient revenue for our full dataset. The associated coefficients suggest that, on average, hospitals that implemented telehealth prior to the COVID-19 pandemic observed increases in revenue ranging from 1.7% (net patient revenue) to 5.59% (outpatient revenue) from 2019 to 2020. However, contrary to our expectations, remote patient monitoring implementation (2019) is significantly associated with decreases in revenue from 2019 to 2020. Note that the negative relationships between remote patient monitoring and revenue are only significant for gross patient revenue and outpatient revenue changes.

When the specifications are explored across subsets of rural and urban hospitals (Tables 3.5 to 3.8), we find that telehealth implementation prior to the COVID-19 pandemic is associated with significant increases in gross patient and outpatient revenue from 2019 to 2020 for both rural and urban hospitals, as hypothesized. Nonetheless telehealth implementation is only associated with significant changes in inpatient and net patient revenue for urban hospitals. Note however that, as we can see in Table 3.9, there is no evidence of significant differences between the estimated coefficients for telehealth implementation for rural and urban hospitals. Therefore, the lack of significance of the estimated telehealth coefficients for rural hospitals could be due to the larger variance (and standard errors) that we find in rural hospitals.

When we explore rural vs. urban hospitals separately, we find, again, that remote patient monitoring implementation prior to the COVID-19 pandemic is associated with decreases in revenue from 2019 to 2020 (Tables 5 to 8). However, the negative relationships between remote patient monitoring implementation and revenue are only significant for gross patient and outpatient revenue for rural hospitals. As we can see in Table 3.9, the estimated coefficients for remote patient implementation are not significantly different for rural and urban hospitals. However, given the larger variance found in rural hospitals, the negative relationship between remote patient monitoring and hospital revenue for rural hospitals could be more significant than our estimates suggest.

6. Discussion

Our results suggest that, as hypothesized, telehealth implementation prior to the COVID-19 pandemic (in 2019) is associated with significant *increases* in gross patient, inpatient, outpatient, and net patient revenue during the pandemic (from 2019 to 2020) for our full dataset (including both rural and urban hospitals). With the largest increases found in outpatient revenue ($2.59\%, P < 0.01$), followed by inpatient and gross patient revenue (both $2.42\%, P < 0.01$), and net patient revenue ($1.70\%, P < 0.01$). However, contrary to our expectations, remote patient monitoring implementation prior to the COVID-19 emergency declaration is significantly associated with gross patient and outpatient revenue *decreases* from 2019 to 2020 ($-1.06\%, P < 0.01$ and $-1.52\%, P < 0.01$).

When we extend the analysis to look at rural vs. urban hospitals separately, we find that for urban hospitals, telehealth implementation is significantly associated with increases in gross patient ($2.26\%, P < 0.01$), inpatient ($2.55\%, P < 0.01$), outpatient ($3.00\%, P < 0.01$), and net patient ($1.90\%, P < 0.01$) revenue from 2019 to 2020. However, for rural hospitals, telehealth implementation is only significantly associated with gross patient ($2.32\%, P < 0.01$) and outpatient ($2.25\%, P < 0.05$) revenue increases. We note, however, that there is no evidence of significant differences between the estimated coefficients for telehealth implementation for rural and urban hospitals. Therefore, we hypothesize that the lack of significance of the estimated telehealth coefficients for rural hospitals is a result of the larger variance found in these hospitals.

On the contrary, we find that remote patient monitoring implementation is associated with significant decreases in gross patient ($-1.42\%, P < 0.05$) and outpatient ($-1.89\%, P < 0.05$) revenue from 2019 to 2020, but only for rural hospitals. For urban hospitals, remote patient monitoring implementation is not significantly associated with any revenue changes. Here too, we note that there is no evidence of significant differences between the remote patient monitoring estimated coefficients for rural and urban hospitals. Given the larger variance found in rural hospitals, we hypothesize that the negative relationship between remote patient monitoring and revenues for rural hospitals could be more significant that our estimates suggest.

Our findings are relevant for policy discussion, as telehealth appears to be here to stay. Strong continued uptake, changing consumer and provider perceptions, and changes in the regulatory environment during the COVID-19 pandemic have contributed to telehealth use rates never seen before. However, although the COVID-19 pandemic demonstrated the relevance and the potential of telehealth, going forward, there is still some uncertainty regarding the long-term financial benefits of telehealth implementation. Our study adds to the literature on the effects of telehealth on hospital financial outcomes; and our results support the claims of telehealth advocates that telehealth can be an asset for hospitals and practices aiming to improve their finances.

As an empirical study, our analysis has important limitations. First, we use distinct metrics to measure telehealth and remote patient monitoring implementation. There may be more efficient ways to measure health IT implementation that we did not consider for this study. Second, our metrics measure exclusively whether telehealth and remote patient monitoring have been implemented by the hospital, we have limited insight into its abilities or usage. Data on telehealth and remote patient monitoring abilities and usage could better inform its effects on hospital revenue. Third, our sample is limited by hospitals reporting data on telehealth monitoring implementation to the AHA Annual Survey of Hospitals IT Supplement; we are limited by the self-reported nature of the IT Supplement survey data, which may introduce some measurement error. Fourth, we have limited access to alternative control variables that can be used as predictors of revenue changes. Missing covariates such as quality of care, hospital debts, and executive skills of hospital managers, could introduce bias into our estimated coefficients. Finally, our analysis is subject to the usual cautions about causal inference with observational data.

It is relevant to note that as part of the Coronavirus Aid, Relief and Economic Security (CARES) Act and the Health Care Enhancement Act, Congress gave $175 billion in subsidies to aid hospitals and practices during the COVID-19 emergency. Such aid did not affect our results because hospitals recorded the aid they obtained from the relief fund as "other non-operating income" (Wang, Bai, and Anderson, 2022). Non-operating revenue and expenses include those revenues and expenses not directly related to patient care or patient services (Health Resources and Services Administration, 2021). The revenues we examine on this study represent revenues received from the delivery of health care services directly to patients.

7. Conclusions

The objective of this study is to examine the relationship between early telehealth / remote patient monitoring implementation (before the COVID-19 emergency declaration), and revenue changes during the COVID-19 pandemic (from 2019 to 2020). We hypothesize that hospitals that adopted telehealth and remote patient monitoring before the COVID-19 pandemic were able to respond in a timelier manner to the health emergency and suffered less severe revenue losses during the COVID-19 pandemic, than those who did not. Our results support our hypothesis as they suggest that telehealth implementation prior to the COVID-19 pandemic (in 2019) is significantly associated with increases is revenue during the pandemic (from 2019 to 2020). However, contrary to our hypothesis, our results also suggest that remote patient monitoring implementation is significantly associated with revenue decreases. Additional research is necessary to determine why telehealth implementation is associated with increases in revenue, while remote patient monitoring implementation is associated with decreases in revenue.

Table 3.1. Summary statistics by rural / urban status – Hospitals that implemented telehealth and remote patient monitoring before the COVID-19 pandemic (in 2019)

	Rural	Urban	Total
Hospitals in our dataset	664	1,333	1,997
	(33%)	(67%)	(100%)
Hospitals reporting data on TH implementation	626	1,286	1,912
	(94%)	(96%)	(96%)
Hospitals not reporting data on TH implementation	38	47	85
	(5%)	(3%)	(4%)
Hospitals that implemented TH by 2019	470	946	1,416
	(75%)	(74%)	(74%)
Hospitals that did not implement TH by 2019	156	340	496
	(25%)	(26%)	(26%)
Hospitals reporting data on RPM implementation	592	1,257	1,849
	(89%)	(94%)	(93%)
Hospitals not reporting data on RPM implementation	72	76	148
	(11%)	(6%)	(7%)
Hospitals that implemented RPM by 2019	295	660	955
	(50%)	(53%)	(52%)
Hospitals that did not implement RPM by 2019	297	597	894
	(50%)	(47%)	(48%)

Notes:
[a] TH = Telehealth.
[b] RPM = Remote patient monitoring.
[c] Percentages in parenthesis.

Table 3.2. Summary statistics by rural / urban status – Hospitals that experienced revenue increases or decreases during the COVID-19 pandemic (from 2019 to 2020)

	Rural	Urban	Total
Hospitals in our dataset	664	1,333	1,997
	(33%)	(67%)	(100.00%)
Hospitals reporting gross patient revenue	664	1,333	1,997
	(100%)	(100%)	(100%)
Hospitals experiencing gross patient revenue decreases	389	585	974
	(59%)	(44%)	(49%)
Hospitals experiencing gross patient revenue increases	269	695	964
	(41%)	(52%)	(48%)
Hospitals reporting inpatient revenue	664	1,333	1,997
	(100%)	(100%)	(100%)
Hospitals experiencing inpatient revenue decreases	404	548	952
	(61%)	(41%)	(48%)
Hospitals experiencing inpatient revenue increases	254	732	986
	(38%)	(55%)	(49%)
Hospitals reporting outpatient revenue	664	1,333	1,997
	(100%)	(100%)	(100%)
Hospitals experiencing outpatient revenue decreases	363	628	991
	(55%)	(47%)	(50%)
Hospitals experiencing outpatient revenue increases	283	504	787
	(43%)	(38%)	(39%)
Hospitals reporting net patient revenue	664	1,333	1,997
	(100%)	(100%)	(100%)
Hospitals experiencing net patient revenue decreases	413	722	1,135
	(62%)	(54%)	(57%)
Hospitals experiencing net patient revenue increases	245	558	803
	(37%)	(42%)	(40%)

Notes:
[a] Percentages in parenthesis.

Table 3.3. Summary statistics by rural / urban status – Percent of hospitals that implemented telehealth / remote patient monitoring before the COVID-19 pandemic (in 2019). Percent of hospitals that experienced revenue decreases during the COVID-19 pandemic (from 2019 to 2020)

	Rural	Urban	Difference	Significance
Hospitals that implemented TH by 2019 (%)	0.751	0.736	-0.015	
Hospitals that implemented RPM by 2019 (%)	0.498	0.525	0.027	
Hospitals that experienced decreases in GPR (%)	0.586	0.439	-0.147	***
Hospitals that experienced decreases in IPR (%)	0.609	0.411	-0.197	***
Hospitals that experienced decreases in OPR (%)	0.547	0.471	-0.076	***
Hospitals that experienced decreases in NPR (%)	0.622	0.542	-0.080	***

Notes:
[a] TH = Telehealth.
[b] RPM = Remote patient monitoring.
[c] GPR = Gross patient revenue.
[d] IPR = Inpatient revenue.
[e] OPR = Outpatient revenue.
[f] NPR = Net patient revenue.
[g] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 3.4. Summary statistics by rural / urban status – Hospital characteristics

	Rural	Urban	Difference	Significance
CMI	1.26	1.57	0.31	***
General hospital status	0.97	0.75	-.22	***
Number of beds 2019	47.24	172.68	125.44	***
Number of beds 2020	46.49	173.61	127.12	***
Number of employees 2019	350.93	1396.07	1045.15	***
Number of employees 2020	346.72	1400.05	1053.34	***
Number of discharges 2019	1782.60	9687.48	7904.88	***
Number of discharges 2020	1662.71	9140.44	7477.74	***
Number of acute days 2019	7558.29	51347.18	43788.89	***
Number of acute days 2020	7134.07	49928.28	42794.21	***
Number of beds PC	-0.01	0.00	0.01	**
Number of employees PC	-0.02	-0.01	0.01	
Number of discharges PC	-0.09	-0.06	0.03	***
Number of acute days PC	-0.08	-0.04	0.04	***

Notes:
[a] PC = Percentage change from 2019 to 2020.
[b] $* P < 0.10, ** P < 0.05, *** P < 0.01$.

Table 3.5. Results – Relationship between telehealth / remote patient monitoring implementation before the COVID-19 pandemic (in 2019) and gross patient revenue changes during the COVID-19 pandemic (from 2019 to 2020)

Gross patient revenue PC	Full dataset		Rural		Urban	
General beds PC	0.0303	*	0.0546	**	0.0038	
	(0.0162)		(0.0239)		(0.0235)	
Total employees PC	0.2148	***	0.1945	***	0.2112	***
	(0.0197)		(0.0331)		(0.0243)	
Total discharges PC	0.1016	***	0.0700	**	0.1280	***
	(0.0178)		(0.0271)		(0.0239)	
Total acute days PC	0.1538	***	0.1092	***	0.2194	***
	(0.0203)		(0.0285)		(0.0314)	
General hospital	-0.0504	***	-0.0458		-0.0489	***
	(0.0062)		(0.0304)		(0.0072)	
Case Mix Index (2020)	0.0134	***	0.0119		0.0147	**
	(0.0041)		(0.0086)		(0.0057)	
Telehealth (2019)	0.0242	***	0.0232	***	0.0226	***
	(0.0048)		(0.0075)		(0.0061)	
RPM (2019)	-0.0106	***	-0.0142	**	-0.0079	*
	(0.0037)		(0.0063)		(0.0044)	
Cons.	0.0314	***	0.0248		0.0319	***
	0.0065		0.0221		0.0080	
Model P-value	0.0000		0.0000		0.0000	
R-squared	0.3446		0.2685		0.3774	
Number of observations	1,764		577		1,187	

Notes:
[a] PC = Percentage change from 2019 to 2020.
[b] RPM = Remote patient monitoring.
[c] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[d] Robust standard errors in parenthesis.

Table 3.6. Results – Relationship between telehealth / remote patient monitoring implementation before the COVID-19 pandemic (in 2019) and inpatient revenue changes during the COVID-19 pandemic (from 2019 to 2020)

Inpatient revenue PC	Full dataset		Rural		Urban	
General beds PC	0.0080		0.0315		-0.0146	
	(0.0213)		(0.0288)		(0.0202)	
Total employees PC	0.1849	***	0.2118	***	0.1578	***
	(0.0264)		(0.0529)		(0.0214)	
Total discharges PC	0.1018	***	0.0719	*	0.1255	***
	(0.0236)		(0.0409)		(0.0220)	
Total acute days PC	0.4610	***	0.4348	***	0.5058	***
	(0.0288)		(0.0408)		(0.0250)	
General hospital	-0.0502	***	-0.0579	**	-0.0441	***
	(0.0065)		(0.0269)		(0.0064)	
Case Mix Index (2020)	0.0140	**	-0.0070		0.0118	**
	(0.0062)		(0.0164)		(0.0060)	
Telehealth (2019)	0.0242	***	0.0188		0.0255	***
	(0.0060)		(0.0114)		(0.0060)	
RPM (2019)	-0.0028		-0.0011		-0.0032	
	(0.0047)		(0.0099)		(0.0048)	
Cons.	0.0379	***	0.0656	*	0.0416	***
	0.0080		0.0342		0.0085	
Model P-value	0.0000		0.0000		0.0000	
R-squared	0.5071		0.4372		0.5423	
Number of observations	1,764		577		1,187	

Notes:
[a] PC = Percentage change from 2019 to 2020.
[b] RPM = Remote patient monitoring.
[c] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[d] Robust standard errors in parenthesis.

Table 3.7. Results – Relationship between telehealth / remote patient monitoring implementation before the COVID-19 pandemic (in 2019) and outpatient revenue changes during the COVID-19 pandemic (from 2019 to 2020)

Outpatient revenue PC	Full dataset		Rural		Urban	
General beds PC	0.0202		0.0593	*	-0.0133	
	(0.0205)		(0.0326)		(0.0257)	
Total employees PC	0.2144	***	0.1815	***	0.2311	***
	(0.0255)		(0.0396)		(0.0336)	
Total discharges PC	0.0956	***	0.0789	**	0.1125	***
	(0.0231)		(0.0328)		(0.0323)	
Total acute days PC	0.0137		0.0101		0.0258	
	(0.0244)		(0.0339)		(0.0352)	
General hospital	0.0640	***	0.0274	*	0.0551	***
	(0.0147)		(0.0164)		(0.0151)	
Case Mix Index (2020)	0.0140	**	0.0166		0.0234	***
	(0.0054)		(0.0121)		(0.0074)	
Telehealth (2019)	0.0259	***	0.0225	**	0.0300	***
	(0.0065)		(0.0091)		(0.0092)	
RPM (2019)	-0.0152	***	-0.0189	**	-0.0115	*
	(0.0047)		(0.0077)		(0.0060)	
Cons.	-0.0957	***	-0.0547		-0.1105	***
	0.0111		0.0484		0.0136	
Model P-value	0.0000		0.0000		0.0000	
R-squared	0.1518		0.0799		0.1755	
Number of observations	1,568		567		1,001	

Notes:
[a] PC = Percentage change from 2019 to 2020.
[b] RPM = Remote patient monitoring.
[c] $* P < 0.10, ** P < 0.05, *** P < 0.01$
[d] Robust standard errors in parenthesis.

Table 3.8. Results – Relationship between telehealth / remote patient monitoring implementation before the COVID-19 pandemic (in 2019) and net patient revenue changes during the COVID-19 pandemic (from 2019 to 2020)

Net patient revenue PC	Full dataset		Rural		Urban	
General beds PC	0.0388	**	0.0496	*	0.0227	
	(0.0167)		(0.0268)		(0.0213)	
Total employees PC	0.2154	***	0.2362	***	0.1911	***
	(0.0180)		(0.0298)		(0.0226)	
Total discharges PC	0.1039	***	0.0628	**	0.1355	***
	(0.0180)		(0.0282)		(0.0233)	
Total acute days PC	0.1289	***	0.1089	***	0.1694	***
	(0.0190)		(0.0279)		(0.0264)	
General hospital	-0.0248	***	-0.0036		-0.0247	***
	(0.0055)		(0.0219)		(0.0067)	
Case Mix Index (2020)	-0.0049		-0.0190	*	-0.0039	
	(0.0048)		(0.0114)		(0.0064)	
Telehealth (2019)	0.0170	***	0.0103		0.0190	***
	(0.0051)		(0.0084)		(0.0064)	
Remote patient monitoring (2019)	-0.0028		-0.0062		-0.0002	
	(0.0042)		(0.0072)		(0.0051)	
Cons.	-0.0198	***	0.0158		0.0199	
	0.0073		0.0252		0.0089	**
Model P-value	0.0000		0.0000		0.0000	
R-squared	0.2427		0.2221		0.2583	
Number of observations	1,764		577		1,187	

Notes:
[a] PC = Percentage change from 2019 to 2020.
[b] RPM = Remote patient monitoring.
[c] $* P < 0.10, ** P < 0.05, *** P < 0.01$.
[d] Robust standard errors in parenthesis.

Table 3.9. Tests of differences between regression coefficients for rural vs. urban hospitals

	t	$P > (t)$
Ho: $TH_{Rural} = TH_{Urban}$		
Gross patient revenue PC	0.06	0.948
Inpatient revenue PC	-0.58	0.563
Outpatient revenue PC	-0.59	0.553
Net patient revenue PC	-0.82	0.964
Ho: $RPM_{Rural} = RPM_{Urban}$		
Gross patient revenue PC	-0.8	0.423
Inpatient revenue PC	0.22	0.829
Outpatient revenue PC	-0.73	0.467
Net patient revenue PC	-0.68	0.498

Notes:
[a] TH = Estimated coefficient for telehealth implementation.
[b] RPM = Estimated coefficient for remote patient monitoring implementation.

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APPENDICES

Appendix 1A. EHR survey question detail (2016 – 2019)

<u>Metric (1): Certified EHR</u>

2018 AHA IT Survey Question #18: "Do you possess an EHR system that has been certified? Certified refers to meeting federal requirements per the Office of the National Coordinator for Health Information Technology (ONC)."

Choices: Yes, No, Do Not Know

<u>Metric (2): EHR functionality</u>

2018 AHA IT Question # 1: "Does your hospital currently have a computerized system which allows for:

Electronic clinical documentation (6 functionalities listed in Appendix 1B)

Results viewing (6 functionalities listed in Appendix 1B)

Computerized provider order entry (5 functionalities listed in Appendix 1B)

Decision support (6 functionalities listed in Appendix 1B)

Other functionalities (4 functionalities listed in Appendix 1B)"

Choices for each functionality: Yes, No, Do not know

Metric (3): EHR use

2018 AHA IT Survey Question # 25: "Please indicate whether you have used electronic clinical data from the EHR or other electronic systems in your hospital to: (check all that apply)

- Create a dashboard with measures of organizational performance
- Create a dashboard with measures of unit-level performance
- Create individual provider performance profiles
- Create an approach for clinicians to query the data
- Assess adherence to clinical practice guidelines
- Identify care gaps for specific patient populations
- Generate reports to inform strategic planning
- Support a continuous quality improvement process
- Monitor patient safety (e.g. adverse drug events)
- Identify high risk patients for follow-up care using algorithm or other tools."

Source: American Hospital Association (AHA) Annual Survey of Hospitals Information Technology Supplement, 2016-2019.

Appendix 1B. EHR computerized system functionalities

Category	Computerized system functionalities
Electronic clinical documentation	Physician notes Nursing notes Problem lists Medication lists Discharge summaries Advanced directives
Results viewing	Radiology images Diagnostic test results Diagnostic test images Consultant reports Laboratory tests Radiology tests
Computerized provider order entry	Laboratory tests Radiology tests Medications Consultation requests Nursing orders
Decision support	Clinical guidelines Clinical reminders Drug allergy alerts Drug-drug interaction alert Drug-lab interaction alert Drug dosing support
Other functionalities	Bar coding for medication tracking Bar coding / RFID for supply chain Telehealth Remote patient monitoring

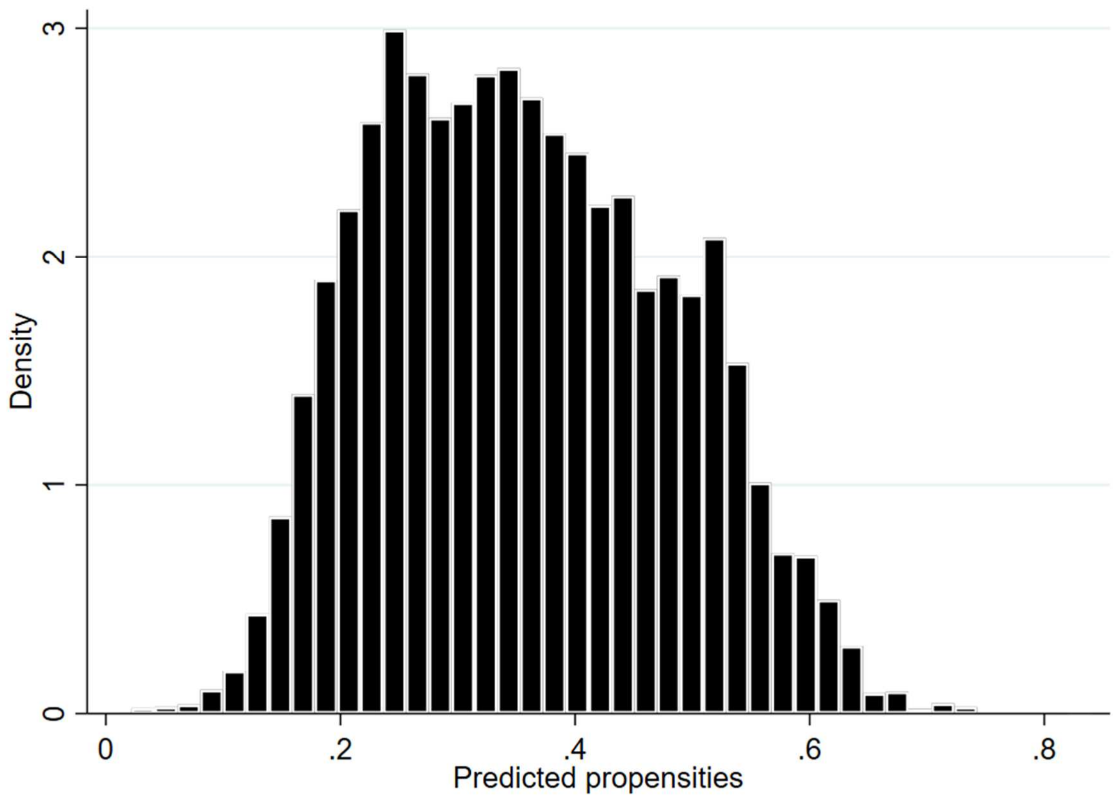
Appendix 1C. Propensity of AHA IT survey response

Logistic regression results

AHA response	Coef.	Std. Err.	z	P>|z|
Case mix index	-0.1748	0.0597	-2.93	0.003
Log of number of beds	-0.0070	0.0340	-0.21	0.836
Log of total employees	0.2922	0.0358	8.17	0.000
Log of total discharges	0.4517	0.0794	5.69	0.000
Log of total acute days	-0.2931	0.0741	-3.96	0.000
Rural Hospital	-0.0558	0.0429	-1.30	0.193
Critical Access Hospital	0.3223	0.0567	5.69	0.000
Ownership-proprietary	-0.1460	0.0567	-2.57	0.010
Ownership-nonprofit	0.3787	0.0410	9.23	0.000
Constant	-3.2114	0.1503	-21.36	0.000
Pseudo R^2	0.0528			
Number of observations	19,882			

Appendix 1D. Propensity of AHA IT survey response distribution

Predicted propensities (AHA response) distribution



Appendix 1E. Summary statistics for control variables, by rural / urban status

	2016		2017	
Variable	Rural	Urban	Rural	Urban
Number of beds	72.19	307.00	71.50	309.39
Case mix index	1.20	1.66	1.21	1.67
Total employees	369.26	1,957.66	375.00	1,992.71
Total discharges	1,944.22	14,553.42	1,928.42	14,656.82
Total acute days	7,552.71	70,323.21	7,440.87	70,725.60
Number of observations	655	941	655	941

Source: American Hospital Directory (AHD) database, 2016-2017.

Appendix 1E. Summary statistics for control variables, by rural / urban status cont.

	2018		2019	
Variable	Rural	Urban	Rural	Urban
Number of beds	71.61	310.70	70.45	312.90
Case mix index	1.23	1.70	1.24	1.72
Total employees	402.06	2,017.98	384.83	2,057.52
Total discharges	1,934.72	14,861.34	1,923.33	14,922.19
Total acute days	7,501.69	71,483.07	7,435.03	72,690.47
Number of observations	655	941	655	941

Source: American Hospital Directory (AHD) database, 2018-2019.

Appendix 2A. Sociodemographic variables description and sources

Variable	Description	Source
Population	Unweighted sample count of the population (thousands)	American Community Survey 5-Year Data – Detailed tables
Median age	Median age	American Community Survey 5-Year Data – Detailed tables
Percent elderly	Percent of population 65 years and older	American Community Survey 5-Year Data – Detailed tables
Median family income	Median family income in the past 12 months, year inflation adjusted USD (thousands)	American Community Survey 5-Year Data – Detailed tables
Percent child poverty	Percent of children in poverty	County Health Ranking Measure Data
Percent unemployed	Percent of population age 16 years and older unemployed but seeking work	County Health Ranking Measure Data
Percent uninsured	Percent of population under 65 without health insurance	County Health Ranking Measure Data
Percent less than High School	Percent of population less than a High School graduate	American Community Survey 5-Year Data – Detailed tables
Percent Bachelor's degree or more	Percent of population with a Bachelor's degree or higher	American Community Survey 5-Year Data – Detailed tables
Percent White	Percent of population White alone, not Hispanic or Latino	American Community Survey 5-Year Data – Detailed tables
Percent Black	Percent of population Black or African American alone	American Community Survey 5-Year Data – Detailed tables
Percent Hispanic or Latino	Percent of population Hispanic or Latino	American Community Survey 5-Year Data – Detailed tables
Percent fair or poor health	Self-reported health—Percent of adults reporting fair or poor health	County Health Ranking Measure Data
Percent obese	Percent of adults that report a BMI $\geq$ 30	County Health Ranking Measure Data
Percent smoking	Percent of adults that report smoking at least 100 cigarettes and that they currently smoke	County Health Ranking Measure Data

Note: American Community Survey 5-Year Data consists of 5-year averages estimates. These estimates are based on data collected over a 5-Year period of time and describe the average characteristics for that period. For instance, 2010 ACS variables are "period estimates" from 2006 to 2010. To perform our analysis, we match these "period estimates" to yearly hospital data. Meaning, we are using 5-year data but assigning it to a specific year.

Appendix 2B. Multilevel Weibull proportional hazards regression using Financial Distress Index (FDI) as control

Time to closure	Coefficient	Hazard ratio
Financial Distress Index	0.3561[a]	1.4276[a]
	(0.0384)	(0.0548)
Median family income (thousands USD)	-0.0533	0.9481
	(0.0268)	(0.0254)
Percent child poverty	-0.1001[a]	0.9047[a]
	(0.0355)	(0.0321)
Percent unemployed	0.3307[a]	1.3921[a]
	(0.0563)	(0.0783)
Percent uninsured	0.1411[a]	1.1515[a]
	(0.0332)	(0.03826)
Percent less than High School	-0.1641	0.8486
	(0.0631)	(0.0535)
Percent White	0.0198	1.0201
	(0.0146)	(0.0149)
Percent Black	0.0315	1.0321
	(0.0152)	(0.0157)
Percent fair or poor health	-0.0214	0.9787
	(0.0398)	(0.0371)
Percent smokers	0.1267[a]	1.1351[a]
	(0.0369)	(0.0371)
Number of observations	9,850	
No. groups state	45	
No. groups hospital	985	
P-value	0.000	

Notes:

[a] Coefficients and hazard ratios statistically significant ($P < 0.05$).

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