THE DETERMINANTS OF TELEHEALTH ADOPTION IN US HOSPITALS

by

Melody Chiang

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Department of Economics

University of Virginia

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Advisor: Amalia R. Miller

Abstract

Telehealth is defined as any medical technology that involves the use of telecommunications to enable interactions and exchange of information between patients and providers. It has been posited to be able to address healthcare disparities by increasing access for medically underserved populations. In this thesis, I investigate the hospital factors and characteristics of patient populations that influence a hospital's decision to adopt telehealth using data on individual hospitals from the American Hospital Association's Annual Survey and Information Technology (IT) Supplement. Using a fixed effects panel regression approach, I find that a hospital's own IT capability and the percentage of other hospitals in the system with telehealth are most strongly associated with telehealth adoption. Conversely, Medicaid telehealth reimbursement laws, private payer laws, and patient population characteristics are not predictive of telehealth adoption in a panel regression. To promote telehealth adoption, policymakers may consider using national policies that encourage health IT implementation in hospitals rather than state-level policies. Additionally, my results suggest that telehealth exhibits network effects, where the technology's value increases as more users in a system adopt it.

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1 Introduction

Telehealth, or telemedicine, is broadly defined as any medical activity that involves an element of distance and the use of telecommunication or computer technology to enable interactions and exchange of information between patients and providers or providers and other providers (Bashshur, 1995; Wootton, 2001). Historically, the aim of telehealth has been to increase access to healthcare for populations in which care has not been available. However, the goals of telehealth have expanded to encompass providing convenience and ultimately reducing healthcare costs (Dorsey & Topol, 2016). Improvements in internet coverage and computer technology have facilitated the increasing spread and scope of telehealth. According to the American Hospital Association's (AHA) Annual Survey, the use of full or partial computerized telehealth in hospitals has grown rapidly. In 2010, 35% of hospitals surveyed had at least some degree of telehealth use, and in 2017, this increased to 76% (American Hospital Association, 2019). Additionally, in 2016, it was estimated that 40-50% of hospitals and 61% of healthcare institutions used some form of telehealth (Office of Health Policy, 2016). The applications of telehealth have also become more diverse, as the range of services available now include treatment of acute conditions like trauma or stroke, primary care, behavioral health, specialty consultations, emergency department services, and intensive care unit services (Chakrabarti, 2019; Dorsey & Topol, 2016).

Telehealth has been posited to have the potential for addressing healthcare disparities by providing increased access to healthcare for medically underserved populations. In particular, rural communities have lower access to health services, healthcare, and health insurance than urban communities (Hirko et al., 2020). Geographic challenges, a shortage of primary care physicians and specialists, and economic barriers to travel all impact access (Marcin et al., 2016). Expanded access to telemedicine, particularly in primary care, could promote early detection of diseases which will ultimately prevent health deterioration, reduce hospital admissions, and reduce costly interventions (Grecu & Sharma, 2019).

Despite the potential upsides of telemedicine, however, there are still structural barriers that need to be addressed to make it an effective solution. A lack of digital technology, literacy, or broadband coverage can drastically limit the ability of telemedicine to be of use to certain populations. These problems, otherwise known as the digital divide, are particularly pronounced in rural areas, as well as for older people of color and those with low socioeconomic status (Velasquez & Mehrotra, 2020). In 2018, 98.5% of urban areas in the U.S. had access to fixed terrestrial broadband, compared to only 77.7% of rural areas and 72.3% of tribal lands (FCC, 2020). These populations that lack access to digital technologies also tend to have worse health outcomes and would benefit greatly from telehealth services if available (Ortega et al., 2020). Additionally, heterogeneous reimbursement policies for telehealth services constitute another challenge for widespread adoption of telehealth. Reimbursement policies across payers like Medicare, Medicaid, and private insurers can vary widely, making it difficult for providers to navigate the complicated policy landscape (Jaffe et al., 2020). Additionally, legal concerns regarding liability issues as well as privacy concerns can negatively impact the willingness of patients and clinicians to use telehealth technologies (Hale & Kvedar, 2014).

The COVID-19 outbreak and the subsequent need for health systems and providers to limit in-person visits has accelerated the adoption and use of telehealth during the pandemic, as nearly all federal, state, and private insurers have expanded telehealth coverage (Campos-Castillo & Anthony, 2020). The dramatic shift to virtual connections and interactions may have exacerbated existing health disparities for rural Americans that lack the infrastructure necessary to use telehealth effectively (Hirko et al., 2020). Telehealth use, measured as percentage of insurance claims billed as telehealth encounters, increased from 0.2% in 2019 to 1.9% in 2020, but older adults aged 45-64 were less likely to use telehealth compared to younger adults aged 18-44, and those in urban areas were more likely to use telehealth compared to those in rural areas (Jaffe et al., 2020). A survey conducted in March 2020 also found that in response to the pandemic, Black respondents were more likely than Whites to report using telehealth (Campos-Castillo & Anthony, 2020). A third study conducted by Pierce & Stevermer (2020) found that in a single healthcare institution in the US following telehealth expansion in response to the COVID-19 pandemic, women, those aged 65 and older, self-pay patients, and patients with Medicaid and Medicare were more likely to have a telehealth visit. Patients that were Black as well as patients in rural areas were less likely to have a telehealth visit. While these studies are limited in scope and may not be completely accurate representations of disparities in telehealth use, they highlight potential disparities and suggest that there may be heterogeneous effects within telehealth use. While it is still unclear whether COVID-19 will permanently alter telehealth usage trends, the pandemic has made the issue of disparities in access to telehealth even more salient.

To investigate the source of the noted disparities in telehealth access, I ask: what factors determine whether a particular hospital decides to implement telehealth programs and services? These factors include hospital characteristics like size, location, system participation, population characteristics, and telehealth-related reimbursement policies. I use a fixed effects panel regression approach to investigate the influence of these factors across hospitals in the US from 2008 to 2017.

I find that the factors that are significantly associated with telehealth adoption, and are robust to the inclusion of hospital and year fixed effects, are hospital IT capability and the share of other hospitals within the same system that have telehealth. I also break down the group of hospitals in the same system as a hospital of interest into the subgroup of hospitals that are both in the system and in the same geographic area and the subgroup that is in the system but outside the geographic area. In this subgroup analysis, I find that the share of hospitals with telehealth that are in the system but outside of the geographic area is the most significant factor influencing telehealth adoption. Prior literature also suggests that membership in a hospital system is associated with telehealth adoption (Adler-Milstein et al., 2014; Burns et al., 2015; Chen et al., 2020). However, my results differ from previous studies that have also found that Medicaid reimbursement policies for telehealth, rurality, and adequate internet access are associated with telehealth adoption, although this is likely due to the use of panel data and fixed effects in my analysis as opposed to the cross-sectional studies conducted previously (Harvey et al., 2018; LeRouge & Garfield, 2013; Neufeld et al., 2015; Schmeida et al., 2007).

This research provides important insights into the interaction between system participation and geographic location in the context of telehealth adoption and suggests that both factors can impact the perceived usefulness of telehealth services. My work contributes to the body of literature that will help future researchers come to a better understanding of how hospitals decide to provide telehealth services. These insights will be a crucial step in addressing the barriers to telehealth adoption. Additionally, the insights derived from this research project can assist in informing policy recommendations aimed at reducing disparities in telehealth access to allow all people to benefit from this technology.

2 Literature Review

The first section of this literature review will discuss a theoretical framework adopted from social sciences that can help elucidate the factors that impact technology adoption. These frameworks will then be applied to a discussion of telemedicine to identify factors specific to telemedicine adoption. The second and third section will review the prior literature on the topic and place the variables impacting adoption in context of the framework discussed earlier. Lastly, the proposed research's contribution to the literature will be discussed.

2.1 Framework for Understanding Technology Adoption

According to E. M. Rogers' theory of the diffusion of innovations, five attributes of innovations that influence the likelihood of adoption include relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2010). These attributes are defined in Table 1. Innovations

Table 1: Definitions of the attributes of innovations that impact adoption (Rogers, 2010).

Attribute	Definition
Relative advantage	The degree to which an innovation is perceived as better than the idea it supersedes.
Compatibility	The degree to which an innovation is perceived as being consistent with the existing values and needs of potential adopters.
Complexity	The degree to which an innovation is perceived as difficult to understand and use.
Trialability	The degree to which an innovation may be experimented with on a limited basis.
Observability	The degree to which the results of an innovation are visible to others.

that are perceived to have higher relative advantage, compatibility, trialability, and observability, as well as less complexity, are likely to be adopted more rapidly. Adoption of technologies, including those in healthcare, are often observed to follow an S-shaped logistic growth curve (Russell, 1977; Zanaboni & Wootton, 2012).

Helitzer et al. (2003) conducted interviews with hospitals in New Mexico about their adoption of telehealth services, and categorized the responses into the attributes described in Table 1. In terms of relative advantage, telehealth was perceived as allowing for accessible consultation of providers with high expertise and is time and cost-efficient compared to current alternatives. If billing mechanisms were in place, telehealth was also perceived to have economic gain. In terms of compatibility, telehealth programs seemed to approximate traditional practice patterns. However, buy-in from administrators, physicians, and nurses would all be needed to promote adoption of this technology. The complexity of adopting telehealth systems was thought to be dependent on the availability of training and technical assistance, but overall, interviewees thought that it was easy to learn how to use the technology. Lastly, telehealth was perceived to have high observability, as the process and results would be visible to others, and high trialability, as telehealth can be applied to different specialties independently of one another.

When considering an individual hospital's decision to adopt telehealth services, the attributes of relative advantage, compatibility, and complexity could be considered most relevant to a cost-benefit analysis. In the next section of the literature review, I identify variables in the prior literature that can impact these three attributes and ultimately, a hospital's decision to adopt telehealth services or not.

2.2 Factors Impacting Adoption of Telehealth Services

Surveys and interviews have identified several factors that contribute to a hospital's decision to adopt telehealth services, including hospital size, location, patient demographics, reimbursement policies, and internet access. Regarding hospital characteristics that can influence telehealth adoption, hospital size has an uncertain impact. Gagnon et al. (2005) observed that smaller hospitals, as defined through number of beds and annual admissions, were more likely to adopt telehealth services due to a lack of specialists. Telehealth services would be necessary for these hospitals to gain access to these specialists. However, smaller hospitals may not have the resources to be able to purchase telehealth capabilities, as implementation of the technology may be less cost effective (Kim et al., 2019). Therefore, telehealth adoption may offer less of a relative advantage for smaller hospitals. Secondly, in terms of location, hospitals located in more remote areas were hypothesized to be more likely to adopt telehealth, as the primary population targeted by telehealth are often those with mobility constraints or face higher transportation costs due to geography (Gagnon et al., 2005; Kim et al., 2019). Hospitals may perceive telehealth services to have a relative advantage when a large proportion of the patient population lives in rural areas. This perception is also reflected in how physicians at remote sites frequently view telehealth as having a relative advantage, but those at central hub sites view telehealth instead as having no relative advantage and requiring changes to current practices and roles (Zanaboni & Wootton, 2012).

Characteristics of the patient populations that a hospital serves are thought to impact a hospital's decision to provide telehealth services as well. First, as discussed in the Introduction, a lack of broadband coverage can reduce the likelihood that telehealth services will be adopted (LeRouge & Garfield, 2013). A lack of internet access can make it more complex for patients and providers to adopt telehealth successfully. It has also been traditionally thought that hospitals serving an older patient population may be less likely to adopt telehealth as older adults may have no interest in the use of technology or are not able to. However, while younger adults use a greater breadth of technologies than older adults, Olson et al. (2011) observed that the frequency of searching for health information did not differ between older and younger adults, suggesting that healthcare may be a domain of Internet use which does not differ significantly by patient age (Greenwald et al., 2018; Olson et al., 2011). Overall, the literature suggests that patient age has an uncertain impact on telehealth adoption, and further analysis is needed.

To examine the impact of telehealth reimbursement policies on the adoption of telehealth, the body of literature surrounding the impact of such policies on telehealth use by patients can provide insights. While the rate of patient use of telehealth services is not the same as the rate of telehealth adoption by hospitals, patient use of these services necessitates the provision of telehealth by hospitals first. It might also be expected that a hospital will be more likely to provide telehealth services if they know that patients will use these services and that providers will be reimbursed by insurance companies accordingly. Regulatory infrastructure that allows for reimbursement of telehealth services is necessary for the compatibility of such services with current payment modes used by hospitals.

Telehealth regulation and policy is largely determined at the state level, which provides a source of variation that researchers can leverage when evaluating the impacts of changes in telehealth regulations. Neufeld et al. (2015) looked at changes in telehealth use after Illinois and Michigan adopted policies in 2012 that expanded insurance coverage for telehealth services. They found that significant jumps in Medicare telemedicine encounters occurred after the changes in telehealth insurance coverages, as the number of encounters increased by 173% and 77.5% in Illinois and Michigan, respectively (Neufeld et al., 2015). Harvey et al. (2018) tracked changes in the use of outpatient telehealth services in states that adopted parity laws that require private insurance companies to provide some level of coverage for telehealth services. Overall, they observed that states with parity laws had a significant increase in the number of outpatient telehealth visits, and controlling for year, the odds of having an outpatient telehealth claim was 29.8% higher in parity states than non-parity states (Harvey et al., 2018). These two studies together demonstrate that changes in telehealth insurance policies that increase reimbursements for telehealth lead to corresponding increases in telehealth use. These studies then suggest that the presence of telemedicine reimbursement laws would increase the likelihood that a hospital would offer telehealth services.

Other factors that could also influence telehealth adoption include the presence of other health information technology (IT) and whether the hospital is part of a hospital system. Telehealth services can be enhanced by accompanying health IT technologies, which helps to coordinate care and reduce costs (Chen et al., 2020). Hospitals may perceive telehealth services to be more compatible with their existing operations if they have already implemented other health IT technologies. Additionally, telehealth adoption among multiple hospitals within a hospital system may exhibit network effects, where technological platforms grow in value as they attract more users over time. One benefit of large hospital systems is thought to be greater coordination of care, as patients can be routed to the most appropriate and lowest cost sites and rates of hospitalization and readmission can be reduced (Burns et al., 2015). Within the context of a system, larger telehealth networks can be beneficial by allowing members to access a larger number of specialists and patients, increasing the relative advantage of the technology. Miller & Tucker (2014) find that hospitals part of larger systems are more likely to exchange electronic health information internally than externally. If similar technologies are needed to share electronic health information and coordinate telehealth visits between patients and providers of hospitals within the same system, then larger system size may promote and facilitate telehealth adoption as well. Therefore, both membership in a system as well as the size of that system may impact a hospital's decision to adopt telehealth services.

2.3 Similar Previous Studies

Schmeida et al. (2007) empirically investigated telehealth adoption at the state level from 1995 to 2003 and considered a variety of factors in their analysis, like political ideology, state resources, the percentage of the population living in rural areas, the percentage of households with Internet access, and the percentage of the population that is 65 years and older. They found that a population with more urban residents and older residents were less likely to adopt telehealth programs. However, an increase in Internet access increased the likelihood of telehealth adoption. Legislative professionalism, where members of the legislature are well paid and think of their job as full time, was also positively associated with telehealth adoption. Schmeida et al. (2007) also attempted to capture the influence of physician and nurse interest groups as well as insurance group strength. To measure these factors, the density of physicians or nurses (defined as the number of physicians or nurses per 100,000 resident populations) was used to represent the strength of physician and nurse interest groups, and insurance group strength was measure by the percentage of the population enrolled in Health Maintenance Organizations (HMOs). Schmeida et al. (2007) found that physician density and nurse density decreased and increased the likelihood of telehealth implementation, respectively, suggesting that healthcare interest groups can also have a significant impact on telehealth adoption.

Adler-Milstein et al. (2014) also investigated the impact of state reimbursement policies, hospital characteristics, and market characteristics on telehealth adoption using the 2012 AHA Annual Survey IT supplement. The authors found that hospitals that are more likely to have telehealth capabilities are teaching hospitals, nonprofit institutions, part of a larger hospital system, and have additional advanced medical technology. Additionally, Adler-Milstein et al. (2014) found that reimbursement policies mandating reimbursement for telehealth by private payers increased the likelihood of telehealth adoption. Medicaid telehealth reimbursement policies did not have a significant effect on telehealth adoption. Rurality was another factor that was associated with telehealth adoption.

In sum, the literature suggests that factors that would likely increase telehealth adoption include remote location, membership in a hospital system, and the presence of telehealth reimbursement laws, and the factors that would likely decrease telehealth adoption include lack of broadband coverage. The factors that have an uncertain impact include hospital size and age of the population. This paper will attempt to confirm the impact of variables that the literature has a consensus on and clarify the directional impact of the variables whose impact is still unclear.

2.4 Contribution

The paper investigates the factors that contribute to a hospital's decision to adopt telehealth services and is largely based off the studies conducted by Schmeida et al. (2007) and Adler-Milstein et al. (2014). Like these two previous studies, the proposed research will attempt to look holistically at a variety of factors, including regulatory, hospital, and population characteristics, that could impact telehealth adoption. However, this study will build upon prior studies by analyzing more recent panel data from 2008 to 2017 to clarify the impact of certain hospital and population factors on telehealth adoption. Another unique aspect of this research is a more in-depth analysis of the interaction between geographic and system factors in impacting telehealth adoption.

3 Methodology

My basic approach is to use a fixed effects panel regression to investigate the effect of hospital and population factors on telehealth adoption:

$$TelehealthAdoption_{i,t} = \alpha + \beta_1\{Hospital_{i,t}\} + \beta_2\{Population_{i,t}\} + h_i + \tau_t + \epsilon_{i,t} \tag{1}$$

The main dependent variable in the analysis is a binary variable, with 1 representing a hospital's adoption of telehealth capabilities and 0 signifying no adoption. In the analysis, the unit of observation is an individual hospital in a particular year. In Equation 1, $\{TelehealthAdoption_{i,t}\}$ represents whether hospital i in year t has adopted telehealth services. $\{Hospital_{i,t}\}$ represents a set of hospital characteristics, including hospital size, type of hospital (not-for-profit, for-profit, etc.), hospital IT capabilities, and whether the hospital is part of a system. $\{Population_{i,t}\}$ represents a set of population characteristics of the hospital service area (HSA) the hospital is in, including the rurality of the county, whether the HSA is considered a health professional shortage area (HPSA), the percentage of the population with broadband coverage, and the percentage of residents over age 65. HSAs are defined as local health care markets for hospital care that are composed of several ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area, and is used as the geographical unit of analysis (Dartmouth Atlas Project, n.d.). τ_t represents time fixed effects, which includes events or policies occurring on a nation-wide scale during a specific year that would affect all hospitals in the sample. Lastly, $\epsilon_{i,t}$ is the error term. β_1 and β_2 (and the corresponding coefficients for each term in the respective sets) are the coefficients of interest. I also run a fixed effects logistic regression on the same equation in addition to the standard ordinary least squares (OLS) regression, as the main dependent variable is binary. Because an S-shaped logistic growth curve is thought to be a good model for technology adoption in healthcare (and telehealth as well), a logit model may be more appropriate for this data than a probit model (Zanaboni & Wootton, 2012).

In the next set of analyses, I add on policy dummies to the fixed effects panel regression framework to investigate the effect of Medicaid telehealth reimbursement laws and private payer laws on telehealth adoption while controlling for hospital and population factors:

$$\begin{aligned} TelehealthAdoption_{i,t} = \alpha + & \beta_1\{Hospital_{i,t}\} + \beta_2\{Population_{i,t}\} + \\ & \beta_3\{Policy_{i,t}\} + h_i + \tau_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

$\{Policy_{i,t}\}$ represents a set of policy dummies that vary by state and include whether the state has a private payer law mandating that private payers reimburse for telehealth care in the same way they would reimburse for in-person care. The other policies of interest are Medicaid telehealth reimbursement laws.

The third set of analyses that I perform involve taking a more detailed look at the impact of system participation on telehealth adoption by comparing whether telehealth adoption in other hospitals in the same system or in other hospitals in the same geographic area have a larger impact. I use the same specification as laid out in Equation 1 but divide system participation into three categories: hospitals in the same system and inside the same HSA, hospitals in the same system but outside the HSA, and hospitals outside the system but inside the same HSA. I also use the percentage of hospitals in each of those three categories that have adopted telehealth, as well as the size of each of those categories, as explanatory variables.

There is a potential endogeneity concern regarding a hospital's decision to adopt telehealth and the percentage of other hospitals in the system with telehealth. Hospitals may be more inclined to adopt telehealth when other hospitals in the same system have existing telehealth services in order to access additional providers and patients. However, the reverse could also be true: other hospitals in the system adopt telehealth in response to the hospital of interest's adoption of telehealth. To address this issue, I use an instrumental variables approach where the percentage of other hospitals in the system with telehealth is instrumented by the average IT capability of those hospitals. The method used to find the IT capability of a hospital is described below in Section 4.1. For the analysis with the subdivision of system participation into three categories, I instrument each category with the average IT capability of that group of hospitals.

The reasoning behind using average IT capability as an instrument is that a hospital would take its own IT capabilities into consideration when deciding to adopt telehealth, but the IT capability of other hospitals in the system would not affect its own decision.

4 Data

4.1 American Hospital Association Annual Survey and IT Supplement

The AHA Annual Survey has been conducted annually since 1946 and it asks hospitals to report data on items like geographic location, control, service, facilities, service utilization, and personnel (Mullner & Chung, 2002). As of 2021, the AHA Annual Survey collects data on more than 6,200 hospitals and more than 400 health systems (AHA, 2021). From the AHA Annual Survey, I assembled a dataset containing observations of a given hospital in a particular year from 2008 to 2017. I collected data on the basic characteristics of the hospital, like geographic location, total number of beds and admissions, insurance status of admittees, teaching hospital status, number of outpatient visits, system membership, and control type (whether the hospital was non-profit, for-profit, or government-operated). Federal hospitals were excluded from the sample, but other public hospitals at the state and county level were retained and labeled “government” controlled in the analysis.

Data on whether a particular hospital has adopted telehealth services are available from the AHA's Annual Survey IT Supplement, which is considered to be a national source of reliable and valid measures of health IT adoption in hospitals (Everson et al., 2014). The year 2011 is not reported in the IT Supplement because of changes in how the AHA named the survey (*AHA IT Supplemental Survey*, n.d.). The data from AHA's Annual Survey can be linked to the IT Supplement through each hospital's AHA Identification Number. The survey asks hospitals to report the extent to which they have implemented telehealth programs on a categorical scale from 1 to 6, with 1 representing full implementation and 6 representing that telemedicine services are not in place and the hospital is not considering implementing. For the purposes of this analysis, I considered any score of 2 or less, meaning that telehealth has been fully implemented in at least one unit of the hospital, to signify that the hospital has telehealth capabilities. In 2017, the coding for this question changed from a scale from 1 to 6 to a scale from 1 to 3, where 1 meant that telehealth was fully implemented across all units, 2 meant telehealth was partially implemented, and 3 meant telehealth was not implemented. For 2017, I considered a score of 1 or 2 as signifying that the hospital had telehealth.

The AHA Annual Survey IT Supplement can also be used to obtain data on the health IT capabilities of a hospital. Technologies surveyed include electronic clinical documentation, computerized provider order entry, and decision support. To incorporate this information into the analysis, an index representing overall health IT adoption was created. To create this index, I first determined the subset of health IT functionalities surveyed consistently from 2008 to 2017. These functionalities were reported on the same categorical scale as the question about telehealth, and I considered a score of 2 or less as meaning that the hospital had that health IT functionality. Each hospital's overall IT index was the sum of all the health IT technologies they had each year, and the maximum score for each year was 17. Higher scores indicate greater adoption of health IT technologies.[1]

4.2 Hospital Service Area Characteristics and Medicaid Telehealth Policies

Data on population characteristics at the county level was obtained through census data. The percentage of the population that was 65 years and older was calculated for every county. Data on internet access at the county level was obtained through the Federal Communications Commission (FCC, 2014). Internet access was defined as the number of residential fixed high-speed connections per 1,000 households, where high-speed connections are those over 2000 kbps in at least one direction. A categorical scale from 0 to 5 was used where 0 meant zero connections per 1,000 households, 1 was zero to 200, 2 was 200 to 400, 3 was 400 to 600, 4 was 600 to 800, and 5 was 800 and higher. In my dataset, I transformed this categorical scale by setting each category equal to the midpoint of the range it represents.

The Rural-Urban Commuting Area (RUCA) codes created by the USDA's Economic Research Service classify each county into one of ten codes representing the degree of urbanization of the area (USDA Economic Research Service, 2019). The RUCA codes are based on the decennial census, and because changes to census methodologies occurred from 2008 to 2017, the RUCA codes from 2010 were used to classify all counties for each year. Another control used was whether a county was designated as a HPSA. I used data from the Health Resources & Services Administration to determine whether a particular county was a HPSA (HRSA, n.d.). I defined

[1] The specific functionalities that compose the IT index are listed in Table A2 in the Appendix. Everson et al. (2014) found that the items included in the IT index have been defined as the components of a comprehensive EHR, and that collectively, they can be used as a measure of the underlying capability of health IT adoption. To see whether certain functionalities are more predictive of telehealth adoption, I repeat the general OLS analysis with hospital and year fixed effects (Table A3). The results indicate that the specific functionalities have heterogeneous effects, although the majority of the functionalities are positively associated with telehealth adoption. The functionalities that are significantly positively associated with telehealth adoption include electronic clinical documentation of physician notes, electronic clinical documentation of medication lists, electronic clinical documentation of advance directives, results viewing of radiology images, results viewing of diagnostic test images, computerized provider order entry of medications, and computerized provider order entry of consultation requests. The functionalities that are significantly negatively associated with telehealth adoption include electronic clinical documentation of nursing assessments and results viewing of diagnostic test results. Future studies may wish to consider differentiating between these different functionalities when assessing the role of hospital IT capabilities.

an HPSA in my data to be a geographic HPSA, a shortage of providers for an entire group of people within a defined geographic area, in terms of primary care.

The above data was obtained at the county and ZIP code level but the geographical unit of analysis that I used to link this data to the AHA data was hospital service area (HSA). To obtain the percentage of the population 65 and older and the internet access of an HSA, I took the population-weighted average of all the counties comprising an HSA. HSAs were designated as rural or an HPSA if at least one county within the HSA was rural or an HPSA.

Information on state Medicaid telehealth-related reimbursement policies was obtained from the Center for Connected Health Policy (CCHP) (CCHP, n.d.). The CCHP also records whether different modalities of telehealth, including live video (LV), store-and-forward (SAF), and remote patient monitoring (RPM), are reimbursed. LV refers to the use of real-time video communication platforms, SAF refers to the asynchronous capture, storage, and transmission of patient health information, and RPM refers to reporting, collection, transmission, and evaluation of patient data using wearable or other electronic devices (Catalyst, 2018). Each state's specific Medicaid policy is highly variable; some states may only reimburse for some specific specialties and their specific definitions for LV, SAF, and RPM may vary as well. The CCHP also has information on whether a state has passed a private payer law, which typically stipulate that private payers must reimburse telehealth services that are equivalent to in-person services to the same degree. When compiling my dataset, I abided by the CCHP's definitions and methodologies for coding a state as having a specific policy or not. The CCHP's data on LV, SAF, and RPM is only available for 2013 and later and does not cover the earlier years of the analysis. Data on private payer laws is only available for 2014 and later. Therefore, in the analysis of the impact of telehealth reimbursement policies on hospital telehealth adoption, the sample is limited to 2014 to 2017.

4.3 Data Description

My entire sample consists of 30,478 observations of hospitals from 2008 to 2017. Table 2 contains summary statistics. Characteristics specific to individual hospitals used in the analysis are listed under "General Hospital Factors". I account for the number of beds of the hospital (as a measure of hospital size) and teaching hospital status, as large hospitals and teaching instutitions are associated with early adoption of new technologies (Hillman & Schwartz, 1985). I also account for the share of inpatient days of Medicare and Medicaid patients in case the payer mix of a hospital has an impact on telehealth adoption due to varying telehealth reimbursement policies. The ratio of outpatient days to inpatient days could also impact telehealth adoption depending on whether a hospital preferentially uses telehealth services for outpatient or inpatient services.

Table 2: Summary statistics for general factors, IT factors, system factors, and HSA characteristics for hospitals surveyed by the AHA.

	count	mean	sd	min	max
General Hospital Factors					
# of beds	30478	172.8884	201.5731	1	2877
# of admissions	30478	7287.842	10078.59	1	151183
Major teaching hospital	30478	.065818	.2479677	0	1
Minor teaching hospital	30478	.3423125	.4744913	0	1
% of inpatient days of Medicare patients	30478	.4845825	.219482	0	1
% of inpatient days of Medicaid patients	30478	.1951236	.1686655	0	1
Ratio of outpatient visits to inpatient days	30478	8.707848	88.87514	0	10745.4
Nonprofit hospital	30478	.5940679	.4910796	0	1
Government hospital	30478	.229477	.4205034	0	1
For-profit hospital	30478	.1764551	.3812132	0	1
Hospital IT Factors					
Telehealth	30478	.473325	.4992961	0	1
Presence of EHR	12884	.8146538	.3885932	0	1
Hospital's IT capability	30478	12.23397	6.078552	0	17
System Factors					
# of hospitals in the system	30478	22.10857	40.19229	0	199
Hospital is not in a system	30478	.408557	.4915751	0	1
% of other hospitals in system w/ telehealth	30478	.19834	.284516	0	.9870968
HSA Characteristics					
Households with high-speed internet	30478	659.4412	166.9709	0	900
% of population 65 and older	30478	.1536384	.0377858	.0407468	.4447393
Health professional shortage area	30478	.6188398	.4856798	0	1
Rural	30478	.8167531	.3868752	0	1

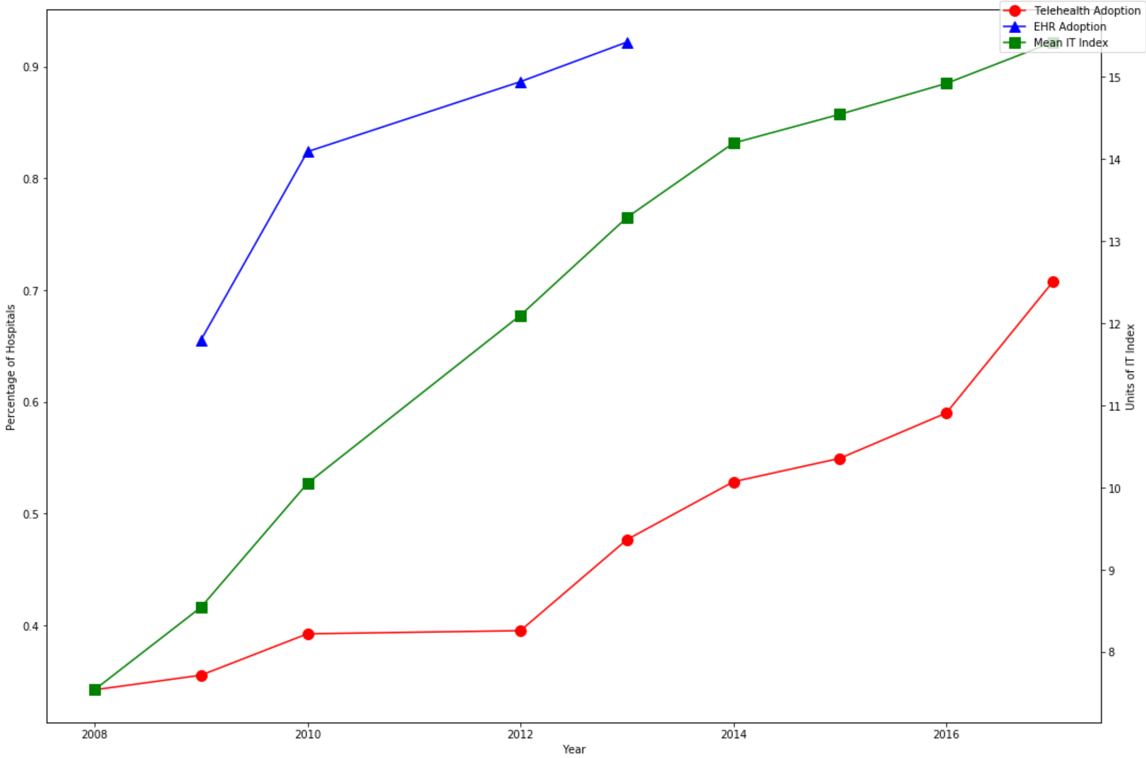

Figure 1: Percentage of hospitals with telehealth and with electronic health records (left y-axis), 2008-2017. The mean IT index for all the hospitals in the sample are plotted as well (right y-axis).

In the sample, about 47% of hospitals were reported to have telehealth. About 81% of hospitals had an electronic health record (EHR) system in place. However, the AHA Annual Survey IT Supplement only directly asked about the presence of an EHR system in the years 2009, 2010, 2012, and 2013, so data on EHRs in hospitals are not available for the entire time period of the analysis. Therefore, in the main analyses performed in this paper, IT index is used as the main indicator of hospital IT capability rather than whether the hospital had an EHR system in place. Figure 1 summarizes trends in telehealth adoption, EHR adoption, and average IT index over time. All three measures generally display an upwards trend over time, with telehealth adoption lagging behind EHR adoption.

Table 3 compares the means for the variables listed in Table 2 for different subsets of the sample: hospitals with telehealth (Column 2) and hospitals without telehealth (Column 3). The variables that do not appear to be significantly different across samples include the share of inpatient days of Medicare patients, the ratio of outpatient visits to inpatient days and the presence of an HPSA in the HSA. The other hospital factors that are significantly different across the two groups generally follow expected trends. Hospitals with telehealth have a larger number of beds compared to those without. A larger percentage of hospitals with telehealth are teaching hospitals and nonprofit compared to hospitals without telehealth. I also find that Medicaid patient

Table 3: Comparison between hospitals with telehealth and hospitals without telehealth.

	(1) Full sample mean	(2) Telehealth mean	(3) No telehealth mean	(4) P-value p
General Hospital Factors				
# of beds	172.9	200.5	148.1	< 0.001
# of admissions	7287.8	8992.2	5756.1	< 0.001
Major teaching hospital	0.0658	0.0886	0.0454	< 0.001
Minor teaching hospital	0.342	0.408	0.283	< 0.001
% of inpatient days of Medicare patients	0.485	0.487	0.482	0.0694
% of inpatient days of Medicaid patients	0.195	0.204	0.187	< 0.001
Ratio of outpatient visits to inpatient days	8.708	8.870	8.562	0.763
Nonprofit hospital	0.594	0.682	0.515	< 0.001
Government hospital	0.229	0.203	0.253	< 0.001
For-profit hospital	0.176	0.115	0.232	< 0.001
Hospital IT Factors				
Presence of EHR	0.815	0.903	0.757	< 0.001
Hospital's IT capability	12.23	14.32	10.36	< 0.001
System Factors Factors				
# of hospitals in the system	22.11	23.13	21.19	< 0.001
Hospital is not in a system	0.409	0.347	0.464	< 0.001
% of other hosp. in system with telehealth	0.198	0.321	0.0884	< 0.001
HSA Characteristics				
Households with high-speed internet	659.4	678.4	642.4	< 0.001
% of population 65 and older	0.154	0.157	0.150	< 0.001
Health professional shortage area	0.619	0.624	0.615	0.110
Rural	0.817	0.829	0.805	< 0.001
Observations	30478	14426	16052	30478

inpatient days make up a larger proportion of inpatient days in hospitals with telehealth. As predicted, presence of health IT, including EHRs, and participation in a system also appears to be more common in hospitals with telehealth. Those hospitals also tend to be parts of systems with a larger share of hospitals with telehealth. Telehealth adoption appears to be greater in rural areas with greater internet access and an older population.

5 Results

5.1 Fixed Effects Panel Regression

The first set of analyses performed investigated the impact of general hospital characteristics, IT factors, system participation, and HSA characteristics on telehealth adoption using a fixed effects panel regression approach (Table 4). The first three columns build in general hospital factors, IT and system factors, and HSA characteristics into the model in that order. Columns 4 and 5 add in hospital and year fixed effects in turn, and Column 5 represents the full model with both hospital and year fixed effects. Robust standard errors are reported for the first five columns and clustered standard errors are reported in Column 6 as a robustness check. Column 7 repeats the full model run in Column 5 using a logistic regression instead of OLS.

Column 3 demonstrates that without adding in hospital or year fixed effects, the share of inpatient days of Medicare patients, the ratio of outpatient to inpatient days, and the number of households with high-speed internet access do not have an impact on a hospital's adoption of telehealth. The coefficients of the other variables included in the model are of the expected sign. Hospital size, teaching hospital status, and nonprofit status are all positively associated with telehealth adoption, which generally agrees with Adler-Milstein et al. (2014). Hospital IT capability and percentage of other hospitals in the system with telehealth are also strongly positively associated, while system size is weakly associated. A 1% increase in the share of hospitals in the system with telehealth increases the likelihood that a hospital will have telehealth by 0.731%. An older population and the presence of an HPSA or rural area is also positively associated with telehealth adoption.

However, when hospital and year fixed effects are included, only hospital IT capability and percentage of other hospitals in the system with telehealth remain significantly associated with telehealth adoption (Column 5). With fixed effects, a 1% increase in the percentage of other hospitals in the system with telehealth results in a 0.675% increase in the likelihood of adoption of telehealth. This general trend makes sense because characteristics like hospital size and teaching hospital status are likely stable and have little variation for a specific hospital from year to year. It is important to note that while these factors may not have causal impacts on a hospital's decision to implement telehealth, they are still significantly associated with telehealth adoption in cross-sectional manner. The fixed effects panel regression methodology used in this paper is limited in its ability to capture the importance of these variables.

Table 4: Hospital IT capability and percentage of other hospitals in system with telehealth predict telehealth adoption.

	(1) Telehealth	(2) Telehealth	(3) Telehealth	(4) Telehealth	(5) Telehealth	(6) Telehealth	(7) Telehealth
# of beds	0.000174***	0.0000980***	0.000116***	0.0000949	0.0000833	0.0000833	0.00149**
	(0.0000179)	(0.0000163)	(0.0000164)	(0.0000822)	(0.0000831)	(0.0000831)	(0.000577)
Major teaching hospital	0.0198	0.0431***	0.0460***	-0.00831	-0.00423	-0.00423	-0.0394
	(0.0136)	(0.0123)	(0.0123)	(0.0357)	(0.0358)	(0.0358)	(0.245)
Minor teaching hospital	0.0699***	0.00887	0.0129*	0.00910	0.00401	0.00401	0.0909
	(0.00700)	(0.00627)	(0.00629)	(0.0130)	(0.0131)	(0.0131)	(0.0837)
% of inpatient days of Medicaid patients	0.172***	0.0867***	0.0717***	0.0403	0.0396	0.0396	0.285
	(0.0199)	(0.0183)	(0.0183)	(0.0353)	(0.0352)	(0.0352)	(0.235)
% of inpatient days of Medicare patients	0.153***	0.0101	-0.00776	0.0339	0.0358	0.0358	0.278
	(0.0152)	(0.0142)	(0.0144)	(0.0306)	(0.0306)	(0.0306)	(0.197)
Ratio of outpatient visits to inpatient days	0.0000280	-0.00000656	-0.00000122	0.0000266	0.0000280	0.0000280	0.000345
	(0.0000319)	(0.0000234)	(0.0000225)	(0.0000344)	(0.0000351)	(0.0000351)	(0.000405)
Nonprofit hospital	0.201***	0.0836***	0.0744***	-0.00922	-0.0138	-0.0138	-0.0324
	(0.00742)	(0.00814)	(0.00823)	(0.0339)	(0.0340)	(0.0340)	(0.200)
Government hospital	0.115***	0.0763***	0.0623***	0.0281	0.0250	0.0250	0.192
	(0.00862)	(0.00925)	(0.00949)	(0.0410)	(0.0409)	(0.0409)	(0.237)
Hospital's IT capability		0.0186***	0.0182***	0.0109***	0.0104***	0.0104***	0.0670***
		(0.000511)	(0.000523)	(0.000833)	(0.000868)	(0.000868)	(0.00580)
# of hospitals in the system		0.000221**	0.000191*	-0.000194	-0.000256	-0.000256	0.000242
		(0.0000788)	(0.0000789)	(0.000218)	(0.000219)	(0.000219)	(0.00131)
% of other hospitals in system with telehealth		0.738***	0.731***	0.700***	0.675***	0.675***	4.291***
		(0.00889)	(0.00895)	(0.0173)	(0.0176)	(0.0176)	(0.129)
Households with high-speed internet			0.00000151	0.0000246	0.0000403	0.0000403	0.000207
			(0.0000157)	(0.0000231)	(0.0000241)	(0.0000241)	(0.000184)
% of population 65 and older			0.644***	3.348***	1.051	1.051	8.684*
			(0.0720)	(0.346)	(0.642)	(0.642)	(3.616)
Health professional shortage area			0.0276***	-0.0668	-0.0859	-0.0859	-0.919
			(0.00532)	(0.0732)	(0.0774)	(0.0774)	(0.853)
Rural			0.0207**	0.110	0.106	0.106	1.066
			(0.00652)	(0.0638)	(0.0666)	(0.0666)	(0.863)
Constant	0.164***	-0.0887***	-0.198***	-0.476***	-0.119	-0.119	
	(0.0120)	(0.0123)	(0.0194)	(0.0885)	(0.121)	(0.121)	
Hospital Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	30478	30478	30478	30478	30478	30478	21561

OLS (Columns 1 – 6), and logistic (Column 7) regression of the impact of general hospital factors, hospital factors, system factors, and HSA characteristics on telehealth adoption. Robust se in parentheses for Columns 1 – 5. Clustered se in parentheses for Column 6. Regular se for Column 7. * p < 0.05, ** p < 0.01, *** p < 0.001

In the fixed effects logistic regression (Column 7), hospital IT capability, percentage of other hospitals in the system with telehealth, hospital size, and a more elderly population are significantly associated with telehealth adoption as well. The logistic and OLS regressions are similar for the most part. Number of beds is the only variable that is significant in the logistic regression and not the OLS model, and the signs of the coefficients are the same across all variables except for the number of hospitals in the system. The full set of logistic regression analyses are available in Table A1 in the Appendix. Because of the similarities in the results of the OLS and logistic regressions and the relative ease of interpretation of the OLS model, OLS regressions are used for the subsequent analyses described below.

5.2 Analysis of Medicaid Telehealth Reimbursement Policies

The second set of analyses focused on the impact of Medicaid telehealth reimbursement policies and private payer laws on telehealth adoption. Figure 2 summarizes trends in state adoption of these laws. A general upward trend in the adoption of these policies can be observed from 2013 to 2019. LV is the most common Medicaid telehealth reimbursement policy; in 2013, 44 states had Medicaid reimbursement for LV and in 2019 this increased to 50 states and DC. In 2013, only 6 states had a reimbursement policy for SAF or RPM, but in 2019, 14 states had a reimbursement policy for SAF, and 22 states had a reimbursement policy for RPM. The number of states that had a private payer law increased from 22 to 40 from 2013 to 2019.

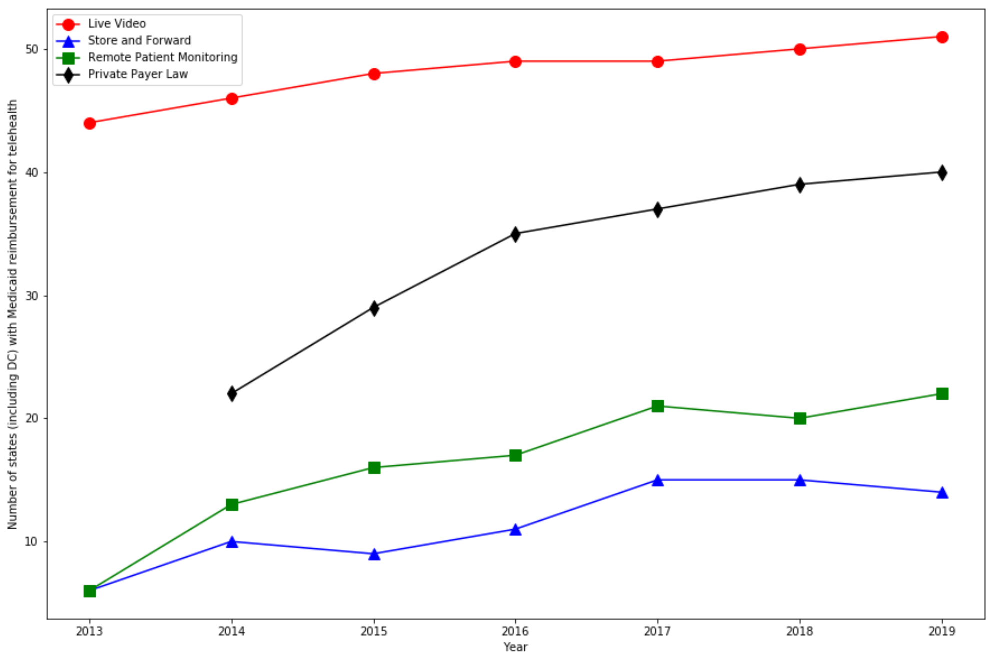

Figure 2: Number of states (including DC) with Medicaid reimbursement policies for different telehealth modalities (LV, SAF, RPM) and private payer laws, 2013-2019.

Table 5 summarizes the results from the fixed effects panel regression investigating the impact of policies regarding telehealth reimbursement. Columns 1 to 3 build in hospital and year fixed effects sequentially with Column 3 representing the full model with both hospital and year fixed effects. In the model without hospital or year fixed effects (Column 1), reimbursement policies for LV and RPM are positively and negatively associated with telehealth adoption, respectively, and the presence of a private payer law is positively associated with telehealth adoption. The sign of the RPM is unexpectedly negative, as the literature generally hypothesizes that any reimbursement policy for telehealth would promote telehealth adoption.

In the full model (Column 3), I find that the percentage of other hospitals in the system with telehealth and the IT capability of the hospital are significantly positively associated with telehealth adoption, which agrees with the results of the general fixed effects panel regression performed in Table 4. However, none of the Medicaid reimbursement policies are significantly associated with telehealth adoption in the full model, although the sign of the coefficients mostly agrees with the hypotheses with the exception of reimbursement policies for LV. The results from this analysis mostly agree with Adler-Milstein et al. (2014), as Medicaid reimbursement policies were found to not be significant in influencing telehealth adoption. However, the insignificance of the presence of private payer laws in this study disagrees with Adler-Milstein et al. (2014) and other previous studies. A potential reason for this discrepancy may be that the time span and scope of this analysis is different compared to prior studies. When investigated across a longer time period and compared with other hospital and geographical factors, private payer laws may no longer be a statistically significant predictor.

Another possibility to consider is that Medicaid reimbursement laws may not be statistically significant in the overall sample because Medicaid patients only make up a small portion of the hospital's patients. As seen in Table 1, the average share of Medicaid inpatient days is around 20%. To account for this, Column 4 repeats the full model with hospital and year fixed effects for the subset of hospitals whose share of Medicaid inpatient days is below the median share and Column 5 is the model run with the subset of hospitals whose share of Medicaid impatient days exceeds the median. However, I find that none of the Medicaid reimbursement laws are statistically significant in Columns 4 and 5. The coefficients for the Medicaid reimbursement laws are also not consistently positive; in Column 4, only the coefficient for reimbursement for RPM is positive and in Column 5, only the coefficient for reimbursement of SAF is positive. Overall, this analysis suggests that state-level policies for telehealth reimbursement, whether it be specifically for Medicaid or for private insurers, are not significantly associated with telehealth adoption.

Table 5: Medicaid reimbursement policies do not impact hospital adoption of telehealth.

	(1) Telehealth	(2) Telehealth	(3) Telehealth	(4) Telehealth	(5) Telehealth
# of beds	0.000144***	0.000120	0.0000955	0.000283	0.000146
	(0.0000231)	(0.000117)	(0.000116)	(0.000285)	(0.000201)
Major teaching hospital	0.0254	0.0298	0.0337	-0.158	0.113
	(0.0173)	(0.0658)	(0.0657)	(0.108)	(0.0803)
Minor teaching hospital	0.0188*	0.0331	0.0242	0.0329	0.0147
	(0.00872)	(0.0287)	(0.0285)	(0.0524)	(0.0337)
% of inpatient days of Medicaid pts	0.0575*	-0.0691	-0.0754	-0.701*	0.0316
	(0.0283)	(0.0593)	(0.0593)	(0.299)	(0.108)
% of inpatient days of Medicare pts	-0.0186	-0.0251	-0.0291	-0.00179	-0.0611
	(0.0223)	(0.0472)	(0.0469)	(0.0642)	(0.122)
Outpatient visits over inpatient days	0.00000821	0.00000218	0.00000336	0.0000172	0.0000264
	(0.0000297)	(0.0000591)	(0.0000563)	(0.0000772)	(0.000123)
Nonprofit hospital	0.0978***	0.0151	0.00128	-0.0249	0.00576
	(0.0131)	(0.0733)	(0.0735)	(0.122)	(0.113)
Government hospital	0.0772***	-0.0284	-0.0357	-0.0219	-0.0817
	(0.0151)	(0.0851)	(0.0844)	(0.153)	(0.128)
Hospital's IT capability	0.0231***	0.0137***	0.0123***	0.00872***	0.0156***
	(0.000986)	(0.00217)	(0.00217)	(0.00257)	(0.00393)
# of hospitals in the sys	0.000134	-0.000150	-0.000260	-0.000464	-0.000294
	(0.000111)	(0.000447)	(0.000444)	(0.000591)	(0.000653)
% of other hosp. in sys w/ telehealth	0.690***	0.667***	0.645***	0.724***	0.598***
	(0.0119)	(0.0292)	(0.0292)	(0.0418)	(0.0429)
Households with high-speed internet	0.0000382	0.0000557	0.0000539	0.0000520	0.0000696
	(0.0000209)	(0.0000292)	(0.0000298)	(0.0000456)	(0.0000412)
% of population 65 and older	0.624***	6.851***	-1.572	-4.588	2.933
	(0.104)	(0.901)	(2.084)	(3.342)	(3.411)
Health professional shortage area	0.0321***	-0.159	-0.0144	0.0990	-0.230**
	(0.00775)	(0.145)	(0.0722)	(0.200)	(0.0840)
Rural	0.0157	0.125	-0.0456	-0.265	0.106
	(0.00937)	(0.0818)	(0.0884)	(0.221)	(0.0613)
Medicaid reimbursement for LV	0.0459*	-0.0450	-0.0479	-0.00540	-0.0696
	(0.0219)	(0.0398)	(0.0397)	(0.0551)	(0.0618)
Medicaid reimbursement for SAF	-0.000757	0.0203	0.0150	-0.00465	0.0453
	(0.00881)	(0.0233)	(0.0233)	(0.0355)	(0.0325)
Medicaid reimbursement for RPM	-0.0157*	0.0224	0.0124	0.0323	-0.0131
	(0.00782)	(0.0206)	(0.0207)	(0.0302)	(0.0301)
Presence of private payer law	0.0267**	0.00846	0.00872	0.00630	0.0148
	(0.00820)	(0.0161)	(0.0163)	(0.0256)	(0.0228)
Constant	-0.344***	-1.020***	0.416	0.980	-0.312
	(0.0381)	(0.164)	(0.350)	(0.611)	(0.544)
Hospital Fixed Effects	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes
Observations	13572	13572	13572	6385	7187

OLS estimates on the impact of Medicaid reimbursement policies, including live video (LV), store and forward (SAF), remote patient monitoring (RPM), and private payer laws on telehealth adoption. Columns 1 – 3 use the full sample, while Column 4 is the subset of hospitals where the % of inpatient days composed of Medicaid patients falls below the median and Column 5 is the subset of hospitals at the median or above. Robust se in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abbreviations: pt = patient, hosp = hospital, sys = system

5.3 Impact of Hospital Systems and Competition within Geographic Areas

The third set of analyses look at whether participation in a system and the behavior of other hospitals in the system were more predictive of telehealth adoption than behavior of other hospitals in the same geographic area. Instead of looking at a single variable capturing the telehealth adoption of all the other hospitals in the same system of the hospital of interest, I break the variable down into three subsets: hospitals outside the HSA of the hospital of interest but in the same system, hospitals inside the HSA and in the same system, and hospitals in the HSA and outside of the system. By doing so, I am able to better investigate whether involvement in a system or competition within a geographical area is more important in influencing a hospital's decision to adopt telehealth. It may be that hospitals within the same HSA that are competing for the same patients will be more likely to adopt telehealth if this additional service attracts more patients.

This analysis is performed using a fixed effects panel regression and the results are in Table 6. Columns 1 through 3 look at whether the number of hospitals involved in each subset predicts telehealth adoption, and Columns 4 through 6 add on the shares of hospitals with telehealth in each of the subsets. Like in the previous analyses, hospital and year fixed effects are added on sequentially so that Columns 3 and 6 are models that include both hospital and year fixed effects. In Column 3, the only variables that appear to be positively associated with a hospital's telehealth adoption is hospital IT capability and the number of other hospitals both in the HSA and in the system. This suggests that the sheer size of a hospital system within a geographical area will influence telehealth adoption. Telehealth adoption may only be perceived as an advantage for a hospital if multiple hospitals in a system are serving the same patient population.

However, when the shares of other hospitals with telehealth are added in (Column 6), the sign of the coefficient of number of other hospitals in the HSA and in the system becomes negative. Hospital IT capability is still predictive of telehealth adoption and older populations are weakly associated with telehealth adoption. The share of hospitals with telehealth outside the HSA but in the system and the share of hospitals with telehealth inside the HSA and in the system are positively associated with telehealth adoption, with a 1% increase in those shares resulting in a 0.466% and 0.313% increase in the likelihood of telehealth adoption, respectively. The share of hospitals with telehealth within the HSA but outside the system does not appear to impact telehealth adoption. This suggests that the network effects associated with telehealth adoption may be a more important factor relative to competition within a geographical area. Telehealth services may only be useful when multiple hospitals within a system have that capability; therefore, it might not be an attractive way to compete with other hospitals in the same HSA unless telehealth services are already common within the hospital system.

Table 6: Comparison of the influence of other hospitals in the same system or in the same geographical area on the telehealth adoption behavior of a hospital of interest.

	(1)	(2)	(3)	(4)	(5)	(6)
	Telehealth	Telehealth	Telehealth	Telehealth	Telehealth	Telehealth
# of beds	0.0000826***	0.000182*	0.000153	0.0000958***	0.0000874	0.0000764
	(0.0000171)	(0.0000897)	(0.0000919)	(0.0000162)	(0.0000851)	(0.0000857)
Major teaching hospital	0.0431**	-0.000807	0.0115	0.0546***	-0.00923	-0.00563
	(0.0132)	(0.0380)	(0.0384)	(0.0124)	(0.0352)	(0.0355)
Minor teaching hospital	0.0264***	0.0330*	0.0206	0.0159*	0.00962	0.00428
	(0.00676)	(0.0141)	(0.0141)	(0.00632)	(0.0131)	(0.0132)
% of inpatient days of Medicaid pts	0.0621**	0.0681	0.0634	0.0636***	0.0383	0.0386
	(0.0192)	(0.0373)	(0.0372)	(0.0184)	(0.0355)	(0.0354)
% of inpatient days of Medicare pts	-0.0306*	0.0383	0.0396	-0.0275	0.0269	0.0294
	(0.0151)	(0.0317)	(0.0317)	(0.0145)	(0.0307)	(0.0306)
Ratio of outpatient visits to inpatient days	0.0000140	0.0000204	0.0000220	-0.00000389	0.0000218	0.0000235
	(0.0000264)	(0.0000347)	(0.0000359)	(0.0000228)	(0.0000322)	(0.0000329)
Nonprofit hospital	0.154***	0.0561	0.0455	0.0813***	-0.00544	-0.0105
	(0.00857)	(0.0353)	(0.0353)	(0.00835)	(0.0344)	(0.0345)
Government hospital	0.121***	0.0590	0.0541	0.0599***	0.0252	0.0223
	(0.00985)	(0.0442)	(0.0439)	(0.00962)	(0.0415)	(0.0415)
Hospital's IT capability	0.0247***	0.0116***	0.00991***	0.0188***	0.0109***	0.0105***
	(0.000522)	(0.000896)	(0.000912)	(0.000521)	(0.000838)	(0.000868)
Households with high-speed internet	0.0000691***	0.0000165	0.0000305	0.00000320	0.0000247	0.0000428
	(0.0000169)	(0.0000257)	(0.0000266)	(0.0000158)	(0.0000233)	(0.0000243)
% of population 65 and older	0.903***	6.774***	1.285	0.574***	3.662***	1.269*
	(0.0798)	(0.360)	(0.684)	(0.0745)	(0.347)	(0.645)
Health professional shortage area	0.0322***	-0.118	-0.153	0.0307***	-0.0669	-0.0857
	(0.00566)	(0.0935)	(0.0962)	(0.00533)	(0.0728)	(0.0768)
Rural	0.0166*	0.0935	0.0957	0.0260***	0.0891	0.0871
	(0.00705)	(0.0716)	(0.0706)	(0.00655)	(0.0682)	(0.0704)
# of other hosp. outside HSA in sys	0.000683***	-0.0000183	-0.000165	0.000522***	0.0000335	-0.0000295
	(0.0000855)	(0.000221)	(0.000223)	(0.0000779)	(0.000216)	(0.000217)
# of other hosp. in HSA in sys	0.0286***	0.0363***	0.0304***	-0.0386***	-0.0453***	-0.0462***
	(0.00365)	(0.00862)	(0.00850)	(0.00383)	(0.00893)	(0.00897)
# of other hosp. in HSA outside sys	-0.00441***	0.00438*	0.00350	-0.00318***	0.00258	0.00228
	(0.000547)	(0.00211)	(0.00211)	(0.000511)	(0.00202)	(0.00202)
% of other hosp. outside HSA in sys w/ telehealth				0.529***	0.485***	0.466***
				(0.00830)	(0.0150)	(0.0151)
% of other hosp. in HSA in sys w/ telehealth				0.297***	0.318***	0.313***
				(0.0111)	(0.0191)	(0.0192)
% of other hosp. in HSA outside sys w/ telehealth				-0.0191*	0.0222*	0.00899
				(0.00795)	(0.0112)	(0.0112)
Constant	-0.183***	-0.851***	-0.0178	-0.162***	-0.491***	-0.121
	(0.0211)	(0.0956)	(0.128)	(0.0201)	(0.0906)	(0.123)
Hospital Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	No	No	Yes	No	No	Yes
Observations	30478	30478	30478	30478	30478	30478

OLS regression on the influence of other hospitals in the system versus other hospitals in the same HSA and in the same system, and other hospitals in the same HSA but outside the system. Robust se in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abbreviations: pt = patient, hosp = hospital, sys = system

To account for the endogeneity concern described in Section 3, the variables concerning the share of other hospitals with telehealth were instrumented by the mean IT capability of those hospitals, and the result from this analysis is summarized in Table 7. Columns 1 through 3 first look at the impact of system participation as an aggregate and the variable of interest is the percentage of other hospitals in the system with telehealth.

In Column 3, I find that similar to the first fixed effects panel regression performed using OLS (Table 3), the hospital's IT capability and the percentage of other hospitals in the system with telehealth are positively associated with telehealth adoption. The coefficient for the percentage of other hospitals in the system with telehealth in the instrumental variables regression, however, is smaller in magnitude than in the OLS regression. In the instrumental variables analysis, a 1% increase in the percentage of other hospitals in the system with telehealth results in a 0.218% increase in the probability of telehealth adoption compared to a 0.675% increase in the OLS regression. This suggests that the OLS estimates are biased upwards and overestimate the impact of the share of other hospitals in the system with telehealth on a hospital's own decision to adopt telehealth.

Column 4 breaks down the group of hospitals within the system into three subgroups, and I find that the share of other hospitals with telehealth outside the HSA but inside the system is the only subgroup that significantly impacts telehealth adoption. These results offer another interpretation of when hospitals perceive telehealth adoption within the hospital system to be beneficial. Telehealth adoption may provide the greatest benefit to a hospital when it allows for access to patients or specialists in another HSA or geographical area. This could be because patients can be physically transferred to other hospitals within the same system in the same geographical area with relative ease. However, telehealth may be the most cost-effective way for a hospital to access the expertise of other specialists when physical travel is too costly or time-consuming.

Table 7: Instrumental variables regression.

	(1) Telehealth	(2) Telehealth	(3) Telehealth	(4) Telehealth
# of beds	0.0000977***	0.000148	0.000128	0.000127
	(0.0000165)	(0.0000850)	(0.0000874)	(0.0000880)
Major teaching hospital	0.0376**	-0.00419	0.00600	0.00698
	(0.0126)	(0.0368)	(0.0372)	(0.0370)
Minor teaching hospital	0.0197**	0.0255	0.0161	0.0167
	(0.00644)	(0.0135)	(0.0136)	(0.0137)
% of inpatient days of Medicaid patients	0.0701***	0.0595	0.0571	0.0568
	(0.0186)	(0.0362)	(0.0363)	(0.0364)
% of inpatient days of Medicare patients	-0.0149	0.0370	0.0387	0.0380
	(0.0146)	(0.0310)	(0.0311)	(0.0312)
Ratio of outpatient visits to inpatient days	0.00000872	0.0000226	0.0000239	0.0000240
	(0.0000244)	(0.0000345)	(0.0000356)	(0.0000357)
Nonprofit hospital	0.131***	0.0357	0.0291	0.0296
	(0.00853)	(0.0345)	(0.0346)	(0.0348)
Government hospital	0.107***	0.0510	0.0475	0.0471
	(0.00965)	(0.0426)	(0.0426)	(0.0428)
Hospital's IT capability	0.0223***	0.0113***	0.0100***	0.0100***
	(0.000552)	(0.000864)	(0.000891)	(0.000894)
# of hosp. in the system	0.000518***	-0.0000559	-0.000172	-0.000106
	(0.0000823)	(0.000217)	(0.000219)	(0.000220)
Households with high-speed internet	0.0000380*	0.0000201	0.0000346	0.0000362
	(0.0000162)	(0.0000243)	(0.0000254)	(0.0000255)
% of population 65 and older	0.836***	5.570***	1.190	1.206
	(0.0744)	(0.390)	(0.662)	(0.667)
Health professional shortage area	0.0296***	-0.0996	-0.131	-0.132
	(0.00544)	(0.0844)	(0.0892)	(0.0886)
Rural	0.0192**	0.113	0.110	0.111
	(0.00672)	(0.0652)	(0.0674)	(0.0671)
% of other hospitals in system with telehealth	0.299***	0.254***	0.218***	
	(0.0189)	(0.0324)	(0.0333)	
% of other hosp. outside HSA in system w/ telehealth				0.172***
				(0.0266)
% of other hosp. in HSA in system w/ telehealth				0.0232
				(0.0383)
% of other hosp. in HSA outside system w/ telehealth				0.00679
				(0.0322)
Constant	-0.209***	-0.720***	-0.0467	-0.0488
	(0.0197)	(0.0933)	(0.125)	(0.125)
Hospital Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Observations	30478	30478	30478	30478

Instrumental variables analysis where the proportion of other hospitals in the system with telehealth is instrumented by the mean IT capability of other hospitals in the system (Columns 1 – 3). In Column 4, the percentage of other hospitals outside the HSA in the system with telehealth, percentage of other hospitals in HSA in the system with telehealth, and percentage of other hospitals in the HSA outside of the system are instrumented for the mean IT capabilities for those groups of hospitals, respectively. Robust se in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Discussion and Conclusion

In this research, I investigate the factors to contribute to a hospital's likelihood of telehealth adoption and find that hospital IT capability and the telehealth adoption behavior of other hospitals within the same system are influential. Factors that appear to be less important in a hospital's consideration of whether to adopt telehealth when taking hospital and year fixed effects into account include the presence of Medicaid reimbursement policies and private payer laws, teaching hospital status, nonprofit status, and public status. Characteristics of the patient population that a hospital serves, like internet access, HPSA status, and rurality, also appear to be less influential and are not consistently significant across the different analyses performed in this thesis. These results somewhat contradict the prior literature; previous studies predict that system participation would increase telehealth adoption but also hypothesize the Medicaid reimbursement laws, remote location, and increased internet access would increase telehealth adoption as well. When the data are analyzed in a cross-sectional manner, however, hospital size, nonprofit status, public status, population age, and presence of an HPSA appear to be significantly associated with telehealth adoption. The fixed effects panel regression method used in this study may not be an optimal strategy to account for the influence of those variables.

One potential reason for the lack of statistical significance of the Medicaid telehealth reimbursement laws may be that Medicaid laws are widely different across states and vary in the specific situations in which reimbursement is mandated. States have different definitions of what kinds of services are considered telehealth, and only some specialist services are covered in specific scenarios. Private payer laws are also determined by states and are subject to the same type of heterogeneity. A policy implication of this conclusion is that state policies may not be effective in promoting telehealth adoption or any type of large-scale change in hospital behavior regarding health IT adoption. Standardized national policies could be potentially more effective in comparison, as federal actions and policies have been observed to encourage and accelerate the rate of adoption of another type of health IT, EHRs (Kolodner et al., 2008).

In this thesis, I identified the percentage of other hospitals within the same system to be one of the most important factors influencing telehealth adoption. However, it is not yet clear whether this association suggests that the act of consolidation actively promotes telehealth adoption as well. Further study of the technology adoption behavior of hospitals before and after entering a hospital system through mergers or acquisitions could shed more light on this question. Even if consolidation of hospitals into systems promotes health IT adoption, this potential benefit must be weighed against potential harms before making broad claims about whether hospital system consolidation bring benefits to patients and consumers overall. Cuellar & Gertler (2005) found that system formation in acute care, nongovernment hospitals in four states from 1995 to 2000 primarily served to increase market power instead of improving hospital efficiency or patient care quality. Before recommending system consolidation as a method for expanding telehealth access and addressing healthcare disparities, further research must be done to clarify the overall impact of hospital systems on patient well-being.

It is also important to acknowledge that this thesis is an exploration of the supply-side factors surrounding hospital telehealth adoption specifically and is limited in generalizability and scope. An analysis of the factors influencing telehealth adoption for other providers of telehealth, including outpatient providers or private practices, could clarify whether the factors identified as predicting telehealth adoption in hospitals are generalizable to other providers. Understanding the demand-side factors, like how patients interact with and utilize telehealth services, is necessary as well. In what scenarios do patients access telehealth most frequently? Do patients typically use telehealth in an outpatient context and interact with providers with whom they already have an established relationship? Or is telehealth more frequently used inside hospitals to allow for consultations with specialists not physically present inside the hospital? Conducting these types of analyses in the future will help establish a more holistic view of the landscape of telehealth and the drivers of telehealth adoption and use among patients and providers.

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Appendix

Table A1: Full fixed effects logistic regression of the impact of general hospital factors, IT factors, system factors, and HSA characteristics on telehealth adoption.

	(1) Telehealth	(2) Telehealth	(3) Telehealth	(4) Telehealth	(5) Telehealth
# of beds	0.000764***	0.000599***	0.000710***	0.00153**	0.00149**
	(0.0000796)	(0.0000882)	(0.0000898)	(0.000581)	(0.000577)
Major teaching hospital	0.0799	0.187**	0.206**	-0.0598	-0.0394
	(0.0578)	(0.0638)	(0.0640)	(0.241)	(0.245)
Minor teaching hospital	0.284***	0.0326	0.0558	0.121	0.0909
	(0.0291)	(0.0329)	(0.0332)	(0.0828)	(0.0837)
% of inpatient days of Medicaid patients	0.731***	0.410***	0.340***	0.237	0.285
	(0.0857)	(0.0956)	(0.0961)	(0.233)	(0.235)
% of inpatient days of Medicare patients	0.655***	0.0446	-0.0503	0.219	0.278
	(0.0680)	(0.0772)	(0.0785)	(0.195)	(0.197)
Ratio of outpatient visits to inpatient days	0.000120	-0.0000391	-0.0000136	0.000302	0.000345
	(0.000133)	(0.000140)	(0.000143)	(0.000393)	(0.000405)
Nonprofit hospital	0.853***	0.423***	0.377***	-0.0314	-0.0324
	(0.0337)	(0.0479)	(0.0484)	(0.198)	(0.200)
Government hospital	0.504***	0.388***	0.316***	0.182	0.192
	(0.0391)	(0.0528)	(0.0539)	(0.235)	(0.237)
Hospital's IT capability		0.0976***	0.0957***	0.0687***	0.0670***
		(0.00296)	(0.00306)	(0.00532)	(0.00580)
# of hospitals in the system		0.00191***	0.00178***	-0.0000494	0.000242
		(0.000475)	(0.000476)	(0.00129)	(0.00131)
% of other hosp. in system w/ telehealth		4.298***	4.277***	4.447***	4.291***
		(0.0824)	(0.0825)	(0.128)	(0.129)
Households with high-speed internet			-0.0000522	-0.00000675	0.000207
			(0.0000878)	(0.000172)	(0.000184)
% of population 65 and older			3.374***	24.92***	8.684*
			(0.386)	(2.079)	(3.616)
Health professional shortage area			0.143***	-0.727	-0.919
			(0.0282)	(0.912)	(0.853)
Rural			0.110**	0.957	1.066
			(0.0357)	(0.879)	(0.863)
Constant	-1.432***	-3.163***	-3.712***		
	(0.0562)	(0.0786)	(0.113)		
Hospital Fixed Effects	No	No	No	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes
Observations	30478	30478	30478	21561	21561

Full logistic regression of the impact of general hospital factors hospital IT factors, system factors, and HSA characteristics on telehealth adoption. SE in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Health IT capabilities composing the IT index

Category	Specific Functionality
Electronic Clinical Documentation	Physician Notes
	Nursing Assessments
	Problem Lists
	Medication Lists
	Discharge Summaries
	Advance Directives
Results Viewing	Lab Reports
	Radiology Reports
	Diagnostic Test Results
	Diagnostic Test Images
	Consultant Reports
Computerized Provider Order Entry	Laboratory Tests
	Radiology Tests
	Medications
	Consultation Requests
	Nursing Orders

Table A3: Decomposition of IT index into individual components.

	(1) Telehealth
Electronic clinical documentation: physician notes	0.0424***
	(0.00944)
Electronic clinical documentation: nursing assessments	-0.0353*
	(0.0141)
Electronic clinical documentation: problem lists	-0.0111
	(0.0110)
Electronic clinical documentation: medication lists	0.0275*
	(0.0123)
Electronic clinical documentation: discharge summaries	0.0119
	(0.0108)
Electronic clinical documentation: advance directives	0.0293**
	(0.00947)
Results viewing: lab reports	-0.0234
	(0.0145)
Results viewing: radiology reports	0.0253
	(0.0162)
Results viewing: radiology images	0.0775***
	(0.0139)
Results viewing: diagnostic test results	-0.0302*
	(0.0137)
Results viewing: diagnostic test images	0.0428***
	(0.0119)
Results viewing: consultant reports	0.0187
	(0.00996)
Computerized provider order entry: laboratory tests	-0.00246
	(0.0226)
Computerized provider order entry: radiology tests	0.00376
	(0.0216)
Computerized provider order entry: medications	0.0355*
	(0.0172)
Computerized provider order entry: consultation requests	0.0464***
	(0.0133)
Computerized provider order entry: nursing orders	-0.0214
	(0.0149)
Constant	-0.113
	(0.123)
Observations	30478

The same general OLS regression with hospital and year fixed effects (Table 4, Column 5) was run in this analysis except the hospital's IT capability has been decomposed into individual functionalities. Only the individual functionalities are shown here.
Robust se in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$