Healthcare across Boundaries: Urban-Rural Differences in the Financial and Healthcare Consequences of Telehealth Adoption

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Abstract

We study the impacts of telehealth adoption on geographic competition among urban and rural healthcare providers, and associated quality of care implications. To causally identify these effects, we consider a quasi-natural experiment: states' entry into the Telemedicine Licensure Compact, wherein participating states coordinate to streamline licensing for physicians wishing to provide telehealth services across state lines. We first show that affected physicians receive more state licenses and earn higher Medicare payments, thereby establishing the Compact entry shock's validity and its positive effect on telehealth adoption. We then examine the heterogeneous effects on provider earnings and quality of care across urban and rural areas. We report evidence that urban providers are systematically more likely to respond to the policy change and financially benefit from it by expanding their service scope to a wider geographic market. As urban providers begin to offer their services to rural patients, rural physicians and hospitals experience a decline in patient volumes, and a revenue loss in turn. We subsequently consider parallel impacts on patient quality of care, and we discuss the implications of our results for healthcare providers and government.

Keywords: Telehealth, Physician Licensure, Medicare Payment, Hospitals, Healthcare Qualities, Telemedicine.

1 Introduction

Telehealth technologies have the potential to transform healthcare delivery and access to care, particularly among rural patients. Several studies provide evidence that telehealth can lower healthcare delivery cost and improve quality of care (Hersh et al., 2001; Jennett et al., 2003). However, with rare exception (Rajan et al., 2013), work examining the implications of these technologies for competition among healthcare providers is lacking. This is notable, as past evidence indicates that competitive concerns are one of the important considerations in

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providers' decisions to adopt telehealth services (Merchant et al., 2015). Understanding the competitive implications of telehealth technologies is important because this has downstream consequences for the performance and sustainability of rural providers, as well as the quality of care experienced by patients in different disease groups, e.g., chronic versus acute care.

Information technologies, and the internet, in particular, have disrupted numerous industries in recent decades. Digital disintermediation has featured prominently in these industry shifts, as consumers increasingly allocate their preferences toward technologically coordinated, online modes of delivery. The story is, in many ways, the same with telehealth technologies; as availability expands and as the quality of telehealth services improves, the competitive position of rural providers is likely to erode (Rajan et al., 2013). With these prospects on the horizon, healthcare administrators lack guidance on where, when, and how telehealth services are likely to shift competition patterns and patient experiences in healthcare delivery. We seek to inform those relationships with this work. In so doing, we shed light on the recent trend in rural hospital bankruptcies and closures, improving our understanding of how technological shifts contribute to rural providers' financial losses. We also address recent calls in the medical literature for research on the relationship between telehealth expansion and quality-of-care, examining whether and to what extent adopting providers maintain their ability to supply adequate care for new, remote patients as well as existing inpatients.

More formally, we address the following questions in this work: How do patterns of telehealth technology adoption affect competition and the relative financial performance of healthcare providers across geographic regions? What implications do the resulting competitive shifts have for the patient experience and quality of care?

Answering these questions requires that we overcome several empirical challenges. First, healthcare markets vary substantially across geographies, in terms of price, the prevalence of disease types (and thus different treatment procedures), and health outcomes (e.g. Chandra and Staiger, 2007; Gottlieb et al., 2010; Finkelstein et al., 2016). The adoption of telehealth technologies is thus an endogenous decision, possibly driven by providers' local conditions. Accordingly, to draw meaningful causal inferences, it is necessary to identify an exogenous source of variation in telehealth adoption.

To this end, we rely on states' staggered entry into the Telemedicine Licensure Compact (the Compact), beginning in 2015, as a quasi-natural experiment, wherein entry events incentivize providers to adopt telehealth technology and engage in telehealth service delivery. As we explain in greater detail in Section 3.1, when a provider's home state joins the Compact, her cost of acquiring licenses to practice medicine in other Compact member states is substantially reduced. This is because the Compact enables healthcare providers who live in one member state to obtain licenses in all *other* member states through a single, streamlined, faster application process. Providers residing in Compact member states are thus able to circumvent the repetitive, heterogeneous licensure application requirements imposed by different states, as well as associated processing times. Upon entering the Compact, a state's providers thus gain readier access to a wider geographic scope of patients, yielding greater financial benefits from telehealth technology adoption.[1]

Second, to arrive at a robust, comprehensive, and generalizable understanding of urban-rural dynamics that arise from telehealth adoption, we must integrate data pertaining to multiple stakeholders, including physicians, hospitals, and patients, across a variety of settings. We thus construct an integrated sample that pertains to almost 140,000 medical doctors, documenting their state licensures, Medicare service delivery, and payments received between 2013 and 2018. We then supplement that sample with detailed information on the financial performance and patient satisfaction associated with more than 4,800 Medicare hospitals. Finally, we capture patient health outcomes by incorporating mortality measures associated with seven major chronic diseases in 1,405 counties.

We first assess the validity of the Compact entry as an exogenous shock to the supply of telehealth services. We quantify a significant rise in affected physicians' applications for additional state licenses, and in the payments they receive from Medicare, implying growth in out-of-state service delivery. We interpret this result as evidence that the Compact extends the telehealth service scope to other member states, and increases adopters' service frequency and financial payoff. To further confirm that the Compact's influence relates directly to telehealth expansion, we examine heterogeneity in the observed effects across affected physicians, based on their access to physical telemedicine infrastructure. We show that the aforementioned licensure growth and financial rewards manifest most strongly among physicians whose affiliated hospitals have fully implemented telehealth services at the time of their state's entry into the Compact. We also rule out the alternative explanation that the Compact affects physicians residing on state borders, who can easily travel to neighboring states to deliver in-person services. In particular, we observe consistent results when we limit our attention to physicians who reside in a state interior. Moreover, we observe no evidence that physicians who reside along state borders exhibit a larger response.

After establishing the validity of Compact entry as a shock to telehealth adoption, we subsequently demonstrate that patterns of adoption and associated financial benefits are very different between urban and rural providers. We find that only affected urban physicians are

[1] Although entry into the Compact is not a provider decision, and thus selection concerns may be reduced, the concern remains that state medical boards may somehow select into the Compact in an endogenous manner. Accordingly, we first alleviate self-selection concerns by verifying that observed geographic, economic, and healthcare market characteristics do not predict whether or when a state enters.

more likely to obtain out-of-state licenses. Financially, affected urban providers experience a systematic increase in Medicare service activity, patient volumes, and payments. We estimate that affected urban physicians' claimed Medicare payments increase by 1.9%, that urban hospitals' patient flows increase by approximately 3.9%, and their revenues rise by 2.6%. On the contrary, we estimate that affected rural providers experience declines in all these dimensions. We estimate that rural physicians' claimed Medicare payments decrease by 5.6%, and that rural hospitals experience a 3.2% decline in patient volumes annually, as well as a 4.6% decline in revenues. These estimates are consistent with a substitution effect (Ayabakan et al., 2020), wherein rural inpatients transition into urban (telehealth-mediated) outpatients. Our estimates are also consistent with a gateway effect (Bavafa et al., 2018), wherein rural patients then follow up on their virtual (outpatient) visits with in-person (inpatient) visits to urban providers.

Collectively, these findings suggest a revenue shift as a result of telehealth expansion, consistent with some anecdotal evidence.[2] In the absence of telehealth options, rural patients may be forced to obtain their healthcare services from local, rural healthcare providers, due to excessive travel costs associated with visiting urban providers. Telehealth technologies can disrupt that status quo by reducing geographic barriers to care, exposing rural hospitals to more severe competition from their urban counterparts. In turn, rural hospitals' patient volumes and revenues decline, cannibalized by urban hospitals. This result raises the concern that telehealth services may further exacerbate pre-existing concerns about the financial health and sustainability of rural hospitals in the United States.[3]

Following our analysis of the financial impacts of telehealth expansion, we investigate effects on the quality of healthcare delivery, from multiple angles. First, we show that physicians are more likely to engage in telehealth service delivery, *a priori*, when they are of higher quality. Specifically, we show that a physician is more likely to apply for additional state licenses when she has never received any disciplinary actions by a medical board, and/or when she has higher online ratings. Despite this, it is not clear whether physicians can maintain service quality after they begin to deliver services via telehealth technology, because the shift to telehealth services means treating more patients, and doing so while learning to operate in a new medium, both of which raise the potential for error. Accordingly, we also consider the effects of the shock on actual treatment outcomes, at both the hospital and county levels. We

[2] Wall Street Journal: "A Cancer Patient's Brutal Commute." (`https://www.wsj.com/articles/a-cancer-patients-brutal-commute-11626129627`, last accessed: 2021/07/14)

[3] Many rural hospitals have become financially insolvent since 2005. Indeed, Forbes has recently reported that "one out of four rural hospitals are at risk of closure" (`https://www.forbes.com/sites/claryestes/2020/02/24/1-4-rural-hospitals-are-at-risk-of-closure-and-the-problem-is-getting-worse/?sh=1d565f451bc0`, last accessed: 2021/01/14).

find that rural hospitals experience a slight (statistically insignificant) increase in reported inpatient satisfaction levels, along with significantly reduced rates of mortality and initial treatment failure for pneumonia. In particular, we estimate that an affected rural hospital sees 0.64 fewer re-admissions among pneumonia patients, and 1.24 fewer deaths (a decline of approximately 8% relative to the average). At the county level, affected rural counties also exhibit reductions in mortality across almost all chronic disease groups, including heart attack, Alzheimer's disease, chronic kidney disease, chronic obstructive pulmonary diseases, diabetes, and cancer.

The improvements in rural healthcare quality may derive from two possible sources: i) increases in provider capacity and slack resources, as inpatient volumes decline, and/or ii) a defensive, competitive response, as providers seek to stem their losses.[4] In either case, rural patients appear to receive better treatment and more attention. In contrast, we find deterioration in these same quality measures at urban hospitals and in urban counties, though the effects are smaller in magnitude.

Our findings around urban-rural differences persist under several alternative specifications and robustness checks. First, we show that these urban-rural differences are not driven by time-varying local characteristics, which we account for by employing granular state or healthcare-market fixed effects. Second, we consider a placebo test by focusing on rural regions that have poor broadband penetration. Because high-speed internet is a prerequisite for the utilization of telehealth services, we expect weaker or negligible effects in such areas. Consistent with our expectation, we find *no* evidence that rural physicians located in low-broadband regions suffer financially following their state's entry into the Compact. Again, this is expected because patients in these areas are less able to take advantage of telehealth service channels offered by distant providers. Lastly, we show that our results persist when we also account for states' membership in other non-physician licensure compacts, namely those that exist for nurses and physical therapists.

This paper contributes to the literature on Information Systems and healthcare in several ways. Although some past work has considered patterns of adoption for telehealth technologies, as well as the effects of telehealth technologies on competitive dynamics between urban and rural health providers, such work has been purely theoretical in nature (Rajan et al., 2013, 2019). Our work presents a first empirical examination of the phenomenon, and provides a unique holistic consideration of both the financial and health quality consequences of telehealth technology adoption by healthcare providers. Our results have important implica-

[4]Note that our results based on county-level mortality, in particular, cannot be explained by selection on the part of unhealthy or dissatisfied patients across geographic regions, because county mortality data is recorded on the basis of patients' legal residence at the time of their death (See `https://wonder.cdc.gov/wonder/help/ucd.html#Location`).

tions for policymakers, and yield at least two important follow-on questions. First, how can a rural hospital be integrated into a telehealth delivery system in a manner that maintains its long-term financial solvency? Second, when implementing telehealth services, how can urban providers continue to ensure their patients' satisfaction and quality of care?

Additionally, we contribute by introducing a novel identification strategy and data construction process for the study of telehealth technologies in the United States. Prior literature has relied extensively upon matching and instrumental variable techniques to address endogeneity concerns around telehealth adoption. Further, a majority of previous work has limited its consideration to a single provider, hospital system, or state. With our quasi-experimental research design, we establish states' entry into the Compact as a plausibly exogenous shock to local telehealth adoption, and exploit that shock to identify causal effects across providers' operating in numerous states, across varied geographies and markets. This approach enables the application of an intuitive econometric specification (difference-in-differences) and allows us to combine different sources of healthcare data across various states to generate a comprehensive evaluation.

Lastly, this work improves our understanding of competition in the US healthcare market. The existing literature often measures the degree of competition on the basis of geographic measures, e.g., the Herfindahl-Hirschman Index, with market boundaries defined by distance or travel time (e.g. Dunn and Shapiro, 2014; Cooper et al., 2019). Our results suggest that, as telehealth becomes more widely adopted (a scenario that is already playing out rapidly as a result of the COVID-19 pandemic), measures of competition tied to geographic distance may lose their validity, and our definitions of healthcare markets may need to be revised.

2 Related Work

Our paper builds on several streams of work. First, we build on the literature studying the impacts of telehealth technology on adopting healthcare providers. For example, Bavafa et al. (2018) show that "e-visits" (digital messaging for physicians-patients) can lead to more in-person interactions with existing patients, a result they term the gateway effect. Sun et al. (2020) show that telemedicine availability in New York emergency rooms significantly reduces waiting times and lengths of stay, because remote services provide more flexibility in resource allocation, enabling providers to better address demand surges and supply shortages. Yeow and Huat Goh (2015) show that hospitals can use healthcare IT systems to address resource allocation inefficiencies, thereby reducing hospitalization rates and inpatient waiting times. Relatedly, Ayabakan et al. (2020) use patient visit-level data from a Maryland health system to estimate the effects of telehealth use on treatment costs. Those authors show that chronic disease patients benefit from telehealth in particular. They estimate a reduction of 1.9 outpatient visits over the 30 days following an initial telehealth appointment, indicative of a substitution effect. Ayabakan et al. (2020) also find evidence of a gateway effect for non-chronic patients, as they estimate that inpatient admissions increase by $\sim$45%. More broadly, Salge et al. (2021) show information technology helps hospitals gain and sustain reputation in the media. Wang et al. (2020) demonstrate that physicians' online activities can bring a higher service quantity in offline channels. Our focus in this paper is different as we evaluate telehealth adoption's competition effect, and the results do not come from a single provider system or a single state. In fact, the Compact entry is an *interstate* policy shock that reshapes the competitive landscape beyond state borders. This framework is a novel setting in the telehealth industry whose outcomes are uncertain. For example, a special report on telehealth in the New England Journal of Medicine (Tuckson et al., 2017) mentions "research is needed to better understand the relationship between facilitating interstate licensure and quality-of-care outcomes to protect against any adverse consequences."

Second, we add to a body of literature that has examined how competition in the healthcare market affects hospital performance. Prior literature finds that concentrated markets tend to increase hospitalization prices and reduce service quality (for a complete review, see e.g. Gaynor et al., 2015). Focusing on geographically defined markets, researchers have documented these findings via reduced form regressions (Kessler and McClellan, 2000; Bloom et al., 2015; Cooper et al., 2019) and structural models (Gowrisankaran et al., 2015). However, our paper provides evidence that geographic boundaries on competition are likely to become "fuzzy" with the expansion of telehealth technologies, as competition begins to manifest across regions, e.g., between states. Although some work has examined patterns of cross-market competition (Dafny et al., 2019), that work was focused on the notion of mergers between geographically distant hospitals, and the implications for bargaining power between hospital systems and insurers. Here, we speak to cross-market competition for patients.

Third, and perhaps the most relevant, we contribute to a small body of literature that has studied the impact of telehealth adoption on urban-rural healthcare competition. Rajan et al. (2013) set up a theoretical framework to examine whether telemedicine may give rise to a "winner takes all" phenomenon, as has happened with the digitization of other markets, i.e. whether a leading specialty hospital will capture the entire market share. Those authors show that a telehealth adopter's market share will tend to increase. However, they also show that rural hospitals can retain some market share when technology setup costs are high (particularly for patients), when patients are faced with higher out-of-pocket costs for telemedicine visits, and when in-person follow-up visits are necessary. Relatedly, Rajan et al. (2019) also present a theoretical model, which predicts that telehealth adoption will improve overall social welfare by enabling the accommodation of more patients. However, those authors conclude some patients, namely those who live closer to a clinic, will suffer a loss as their regular provider becomes busier, e.g., shortening visiting time. We build on these prior works by providing an empirical consideration of these relationships. Further, we expand the scope of these prior studies by considering the quality of such healthcare.

Finally, and perhaps most generally, our work contributes to a broader literature in Information Systems on the interaction between digital and physical channels for sales and service delivery (Choudhury and Karahanna, 2008). For example, Forman et al. (2009) examine book sales at Amazon and show that online sales diminish when a brick-and-mortar bookseller opens nearby. More recently, Overby and Forman (2015) examined the introduction of digital sales channels in the market for used vehicles. Those authors reported evidence that the introduction of digital channels increased price transparency and reduced-price dispersion, as buyers used the channel to shift their demand geographically to exploit price differences. These results are consistent with the expectation and recent evidence that telehealth services have a particularly heavy influence on rural patients, given they typically face higher transportation costs to access inpatient healthcare services. Our work thus explores considerations and implications in line with this past work, in the context of healthcare delivery.

3 Research Design

3.1 Telemedicine Compact Shock

In the United States, each state has laws and regulations that govern the practice of medicine. State medical boards oversee these regulations. Medical boards license medical doctors, investigate complaints, and discipline physicians who violate the medical practice act. For both in-person and telehealth patient care, most state laws require that a servicing physician hold a full medical license in her home state and in the state where the patient resides. However, there is no unified model by which state medical boards approach licensure. In addition to completing all three steps of the United States Medical Licensing Examination (USMLE), state medical boards often have other idiosyncratic licensure requirements that they impose on physicians, including citizenship requirements, educational requirements, FBI criminal background check, in-person interviews, board certification, and assessments of mental and physical health. Even if these criteria are met, state medical boards still have complete discretion on license issuance.[5] A typical application takes four to twelve weeks, and in some states, such as California, it takes as long as seven months.[6] Time and effort aside, physicians also have to pay a ∼$500 state application fee.

As a result of these state-specific requirements, state licensure is perhaps the largest single regulatory barrier to telehealth expansion in the United States. Indeed, in February 2012, the American Telemedicine Association hosted a briefing on Capitol Hill and identified the state licensing requirements, rather than technology readiness, as the key barrier to telehealth adoption.[7] During the COVID-19 pandemic, various regulatory efforts (some permanent, others temporary) have been undertaken to relax the licensure requirement and thereby facilitate telemedicine. For example, in March 2020, the U.S federal government announced that doctors would be allowed to practice medicine across state lines through telehealth technologies. Several states such as New Jersey, Connecticut, Illinois, and Massachusetts, have ordered temporary license waivers or expedited approval processes to facilitate telemedicine during the pandemic.[8] Nonetheless, as COVID-19 vaccination in the United States has expanded, several of those waivers are now being terminated, and most providers continue to confront inconsistent, time-consuming, and expensive state licensure requirements.

Recognizing that physicians were increasingly seeking to practice medicine across state lines leveraging telehealth technologies, the Federation of State Medical Boards initiated a discussion of the Telemedicine Licensure Compact in 2013, to streamline the traditional application process for states' medical licenses. This compact was later renamed the Interstate Medical Licensure Compact in 2014, at the time of its introduction. Within the Compact, physicians are qualified to practice medicine across state lines as long as they hold a full, unrestricted medical license in at least one Compact member state, formally referred to as the physician's State of Principal License (SPL). The physician must prove that the SPL is their primary state of medical practice.[9] Designation of an SPL is the primary step in the streamlined licensure application process provided by the Compact. Other requirements include traditional education and certification criteria, which around 80% of U.S. physicians will have already met. In a single application, a physician residing within the Compact may

[5]For example, the Arizona Medical Board reminds physicians, "A license to practice medicine in Arizona is a privilege, not a right. Please do not assume that licensure is a mere formality or that granting of a license is automatic."

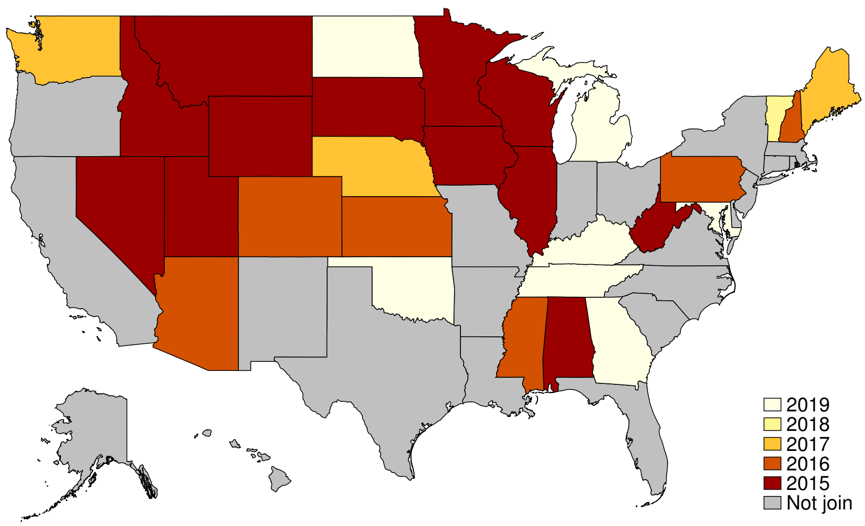
[6]"Physician Licensure Application Fees and Timelines by State," Medicus Healthcare Solutions, February 2019.

[7]"Physician Licensure Barriers to 21st Century Healthcare", the American Telemedicine Association, February 2012.

[8]"U.S. States and Territories Modifying Requirements for Telehealth in Response to COVID-19," Federation of State Medical Boards, November 2020.

[9]For example, the physician can show her primary residence is located in the SPL, or that at least 25% of her practice occurs within the SPL.

Figure 1: Year of States Joining Compact



list other Compact member states for which she wishes to obtain licenses. Subsequently, the SPL verifies her eligibility and shares the information with those other states. In this way, all Compact member states simply rely on each other's license verification processes, to streamline the license acquisition process. On average, it takes just 19 days to acquire all the Compact state licenses.

Member states gradually announced their intention to participate in the Compact after 2015. The timing of member states' entry into the compact is depicted visually in Figure 1. Though the state licenses issued by the Compact permit both in-person and telehealth services, most applicants leverage this process to engage in the delivery of telehealth services. For example, coinciding with the sharp rise in telemedicine delivery during the COVID-19 pandemic, the monthly number of licenses issued by the Compact increased by more than 150% between February and October of 2020 (from 375 to 1,064). Between April 2017 and the end of 2020, the Compact issued more than 20,000 licenses in total.

We leverage states' staggered entry into the Compact as an exogenous shock to the prevalence of telehealth providers in that geography. Because the Compact's application process officially went live on April 6, 2017, we take this quarter as the entry timing for those states that approved their participation in the Compact before that point in time. A possible concern with this identification strategy is self-selection, i.e. states with certain characteristics may endogenously opt to join the Compact. Were this the case, any differences we observe between urban and rural providers' outcomes might be a product of these pre-existing differences, rather than the expansion of telehealth services. We evaluate this possibility in Online Appendix Table A.1. We compare the 30 treated states (including Washington D.C.) with the other 21 control states, along several important dimensions, as of 2014, the year that the

Compact was introduced. We demonstrate there that participating states are geographically dispersed, i.e., they exhibit no obvious clustering. Further, although Medicaid expansions across states may affect hospital revenues, we observe no evidence that Compact members differ from non-members in their expansion of Medicaid in 2014.[10] We also find no significant differences in member states' political preferences, as compared to non-member states, measured in terms of legislative control or the governor's party. Lastly, we find no evidence that Compact member states' populations differ in terms of their economic or health conditions. We also demonstrate that state characteristics do not associate significantly with Compact entry timing. We estimate a Cox Survival Model, which shows the timing of state participation does not depend significantly on any of the above variables. In sum, the treatment and control groups in our analyses exhibit no apparent differences in observable characteristics that might explain or confound our findings. Moreover, we present empirical tests of the parallel trends assumption, which demonstrate no evidence of pre-treatment differences between Compact member and non-member states on several outcomes of interest.[11]

3.2 Data

We collect the data at physician, hospital, and county levels from several sources. The detailed summary statistics of all variables are provided in Table 1. The steps taken to construct our sample are described next.

We first collect physicians' granular licensure information from the Open Payment database. In the U.S., drug companies usually pay promotion payments to physicians for drug usage. Under the Patient Protection and Affordable Care Act (ACA), drug firms must report any physician payment or in-kind "transfer of value" to the Open Payment database. The database starts at August 2013, and we collect the data until December 31^{st} 2018. Each observation in the database is an encounter, i.e. a transaction between a firm and a provider, documenting the company and physician's information, the drug discussed, the dollar amount, and the payment date. Relevant to our project, the company will report up to five state licenses that the physician possesses at the transaction time. We aggregate this information at quarterly frequency, by counting the active number of a physician's unique state licenses in the past two years.[12] Since not all physicians receive payments every quar-

[10]The difference is far from significant ($p = 0.47$). Medicaid expansion cannot explain our results conceptually, in any case, because it would imply effects that run counter to those we observe. Past work by Kaufman et al. (2016) has shown that Medicaid expansions significantly increased rural hospital revenues as compared to urban providers.

[11]As part of our robustness checks, we also present separate estimations by event timing cohort, which yield consistent results. This analysis helps address possible concerns related to the staggered nature of the treatment in our sample (Goodman-Bacon, 2021).

[12]This is because the company sometimes fails to report all licenses, and a standard license is renewed

ter, to alleviate the concerns that our licensure information is not updated in time, we delete those missing more than half of the total observations from 2013Q3 to 2018Q4. From this sample, we also employ physicians' total quarterly promotional payments as a supplementary measure, for a robustness check related to the revenue effects of Compact entry, and thus telehealth expansion.

We then merge the sample with the Centers for Medicare & Medicaid Services (CMS) Physician Compare database, which contains information on Medicare physicians' national provider identifier (NPI), primary operating state, primary specialty, graduation year, and affiliated Medicare hospitals, if any.[13] We require that the hospital affiliation information is non-missing, ensuring that we have control variables associated with the physician's workplace. Lastly, we match the physicians to the CMS Medicare Provider Utilization and Payment Data based on the NPI. It provides information on services and procedures provided to Medicare beneficiaries by physicians, such as the number of services, beneficiaries, and total payments. Unlike the licensure information, the utilization summary is aggregated annually.

Table 1 Panel A summarizes the physician sample. The final physician sample consists of 2,289,126 quarterly observations and 631,047 annual observations associated with 139,696 unique doctors, which represent around 19.4% of all registered physicians affiliated with Medicare hospitals by 2020.[14] We find that roughly 14% of our sample observations are "treated" by state Compact membership. Note that this percentage does not include pre-state membership periods for the eventually-treated doctors. The size of this treatment group is non-trivial; 41,180 physicians, or 29.5% of the physician sample, are working in state that eventually joined the Compact. On average, physicians only apply for 1.38 licenses, and more than half of the physicians solely work in their home state throughout the entire sample period. On average, a physician will provide 6,140 services to 523 Medicare beneficiaries, and receive $193,836 in annual payments ($MedPay_{i,t}$). Note here that, since 2014, CMS applies a standardization process to account for local economic and healthcare conditions when generating the variable $MedStdPay_{i,t}$. Its average is slightly higher ($196,670) than that of the un-adjusted value. Lastly, physicians in our sample receive $972.52 in quarterly average promotional payments from drug companies. The other variables are control variables, which

every one or two years. Our result is robust to using alternative windows, such as the prior half year, year, or five years.

[13] There is no unified identifier between the two databases. We match physicians by first name, last name, middle initial, and require that the primary operating state be reported in the payment information. If the above criteria generate duplicates, we manually search for the doctor's information online to identify the correct match.

[14] Our data is from the Physician Compare database, representing all physicians with CMS. Again, we retain those physicians that have non-missing values for the variable "hosp_afln_1". This step ensures that the physician is associated with a hospital. We then retain records based on unique NPI, resulting in 719,067 physicians.

we explain in the specification section.

Our physician payment information may not be representative of a physician's entire practice as it is limited to information on Medicare fee-for-service beneficiaries. The data are also not intended to indicate the quality of care provided. To address these concerns, we also construct a sample of U.S. hospitals, covering their revenues from all sources and quality measures. Most hospitals are required to provide an annual cost report to CMS in the Healthcare Cost Report Information System (HCRIS), covering information on hospital patient revenues, number of inpatients discharged, income (net patient revenue plus other income), number of beds, the total number of employed staff, and total salary expenditure. Consistent with the physician sample, we collect the data from 2012 to 2018, and restrict the sample to include only short-term acute care hospitals (though our result is robust to including other types of providers). To measure hospital quality, we merge HCRIS data with data from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS), which is a patient satisfaction survey required by CMS, administered to a random sample of adult inpatients experiencing various medical conditions, between 48 hours and 6 weeks after discharge. The core questions on this survey cover the critical aspects of patients' service experience. Among available features, we focus on the overall rating (*Overall*), whether the patient would recommend the service to others (*Recommend*), the helpfulness of staff (*Helpful*), and the informativeness of recovery (*Info*). Because rating scales differ across questions, we calculate the percentage of patients that respond with the highest rating, instead of using average scores. We also include objective measures of treatment, namely the volume of pneumonia deaths (*PNMort*) and unplanned readmissions of pneumonia patients (*PNReadm*).[15] The latter shows the efficacy of initial treatment upon hospitalization; high readmission implies failings in initial service encounters, and translates substantial costs for patients, both physically and financially.

Table 1 Panel B summarizes the hospital sample. Like the physician data, approximately 12.4% of the sample observations are affected by state Compact membership. There are 4,836 unique hospitals in the data, and 2,487 of them are located in Compact states. The average hospital revenue, aggregated over both the inpatient and outpatient services, totals ~$676 million. In terms of geographic locations, hospitals are almost evenly distributed between urban (54%) and rural areas. Lastly, more than 68% of the patients responding to the survey tend to give the highest rating for the aforementioned survey items, and we find that 18.6 (15.8) pneumonia patients are readmitted (die) per year for an average hospital.

Finally, to operationalize healthcare outcomes, we leverage data on patient mortality

[15] The data are from CMS Hospital Compare. We focus on pneumonia because the information for this disease is mostly complete for rural hospitals.

Table 1: Summary Statistics

Variable	Variable Definition	N	Mean	Std. Dev.	Median
Panel A: Physician Sample					
$Compact_{i,t}$	Whether physician i's primary licensed state joins Compact by quarter t	2,289,126	0.143	0.350	0.000
$LicenseNum_{i,t}$	No. of physician i's active state licenses at quarter t	2,289,126	1.384	0.661	1.000
$MedService_{i,t}$	No. of Medicare services by physician i in year t	631,047	6,139.659	25,674.907	1,722.000
$MedBenes_{i,t}$	No. of Medicare beneficiaries receiving physician i's services in year t	631,047	522.607	531.015	379.000
$MedPay_{i,t}$	Medicare payment after applying deductible and coinsurance amounts for provider i's services in year t	631,047	193,835.870	354,691.560	110,444.480
$MedStdPay_{i,t}$	Medicare payment after applying deductible and coinsurance amounts, and standardization for provider i's services in year t	532,734	196,669.950	363,332.470	111,733.550
$TeleScore_{i,t}$	A score with scale one-six for the telehealth and relevant facility level of physician i's working hospital in quarter t	1,506,824	4.604	1.245	5.000
$AdvPay_{i,t}$	Promotion payments of physician i in quarter t	2,289,126	972.518	3,502.929	126.165
$MidSeniority_{i,t}$	Whether physician i has graduated for 10 to 25 years in quarter t	2,289,126	0.468	0.499	0.000
$PastAction_{i,t}$	Whether physician i has received warning by quarter t	2,289,126	0.009	0.096	0.000
$PhyRating_i$	Physician i's online average rating from healthgrades.com collected on 11/21/2020	644,598	4.049	0.806	4.200
$HosRating_{i,t}$	% of patients giving the highest overall ratings in physician i's working hospital the year before her state joined Compact	2,258,742	0.714	0.071	0.720
$HosDischarge_{i,t}$	No. of patients discharged (in 10,000s) from physician i's working hospital in year t	2,280,245	1.936	1.674	1.563
$HosIncome_{i,t}$	Annual income (in millions) of physician i's working hospital in year t	2,280,661	587.104	680.592	376.548
Panel B: Hospital Sample					
Variable	**Variable Definition**	***N***	***Mean***	***Std. Dev.***	***Median***
$Compact_{j,t}$	Whether the state of hospital j joins Compact in year t	27,399	0.124	0.329	0.000
$Rev_{j,t}$	Hospital j's total revenues (in $millions) in year t	27,078	676.286	1,175.439	236.527
$NetRev_{j,t}$	Hospital j's total net revenues (in $millions) after insurers adjust for contractual allowances in year t	27,078	185.405	318.406	76.098
$Discharge_{j,t}$	Hospital j's number of discharged inpatient in year t	27,050	6,856.902	9,601.197	2,892.918
$Salary_{j,t}$	Average annual salary of physicians at hospital j in year t	27,399	60,519.297	20,613.500	60,962.598
$Income_{j,t}$	Hospital j's total income (in $millions) in year t	27,078	200.817	352.810	80.627
$Bed_{j,t}$	Hospital j's number of adult beds in year t	27,068	150.161	312.727	79.000
$PhyNum_{j,t}$	Hospital j's number of staff in year t	27,008	976.989	3,674.273	423.334
$Metro_j$	Whether hospital j is in a metropolitan area	27,399	0.542	0.498	1.000
$Overall_{j,t}$	% of patients giving the highest overall rating for hospital j's service	20,135	71.743	8.844	72.000
$Recommend_{j,t}$	% of patients willing to recommend hospital j's service	20,133	71.519	9.72	72.000
$Helpful_{j,t}$	% of patients giving the highest rating for hospital j's staff helpfulness	20,129	68.189	9.153	67.000
$Info_{j,t}$	% of patients giving the highest rating for hospital j's recovery informativeness	20,129	86.691	4.339	87.000
$PNReadm_{j,t}$	No. of pneumonia unplanned 30-day readmission for hospital j in year t	19,059	18.624	17.221	12.905
$PNMort_{j,t}$	No. of pneumonia 30-day mortality for hospital j in year t	19,001	15.782	14.371	10.941
Panel C: County Sample					
Variable	**Variable Definition**	***N***	***Mean***	***Std. Dev.***	***Median***
$Compact_{k,t}$	Whether the state of county k joins Compact in year t	8,430	0.102	0.303	0.000
$Metro_k$	Whether county k is in a metropolitan area	8,430	0.604	0.489	1.000
$AMI_{k,t}$	No. of deaths from acute myocardial infarction for county k in year t	8,430	50.736	160.003	0.000
$Alzheimer_{k,t}$	No. of deaths from Alzheimer for county k in year t	8,430	115.289	281.637	10.000
$CKD_{k,t}$	No. of deaths from chronic kidney diseases for county k in year t	8,430	116.345	317.621	11.000
$COPD_{k,t}$	No. of deaths from chronic obstructive pulmonary disease for county k in year t	8,430	132.206	279.864	33.000
$Cancer_{k,t}$	No. of deaths from cancer for county k in year t	8,430	146.135	349.908	25.000
$Diabetes_{k,t}$	No. of deaths from diabetes for county k in year t	8,430	114.680	316.003	11.000
$HF_{k,t}$	No. of deaths from heart failure for county k in year t	8,430	162.655	362.799	38.000
$population_{k,t}$	County k's population in year t	8,430	209,496	465,440	78,527
$unemploy_{k,t}$	County k's unemployment rate in year t	8,430	6.298	2.276	5.900
$ND_{k,t}$	County k's natural deaths in year t	8,430	1,696.859	3,130.110	761.000

at the county level. We collect data on yearly deaths due to acute myocardial infarction, Alzheimer's disease, chronic kidney disease, chronic obstructive pulmonary disease, cancer, diabetes, and heart failure for 1,405 counties between 2013 to 2018. These 1,405 counties report mortality data to CDC WONDER for individuals who were legal residents of the county at their time of death, for each of the seven diseases, without missing. Notably, these counties represent approximately half of the total 3,006 counties in the United States. Table 1 Panel C summarizes the county sample.

3.3 Conceptual Framework

Our main hypothesis is that the Telemedicine Licensure Compact will increase the number of physicians providing telehealth services in treated states. The increased adoption will change the competitive landscape in a local healthcare market. In particular, there will be a shift from rural in-person services to urban telehealth services. To show this, imagine that a physician's net benefit from providing telehealth services is characterized by the following function:

$$V = \sum_{t=0}^{+\infty} \delta^t r_t - C,$$

where $\delta < 1$ is the discounting factor, r_t is the expected net profit from telehealth services in time t, and C is the fixed cost of adoption, including the cost of setting up equipment and the effort to learn about the new technologies. A physician will start to provide the services only if the net benefit V is positive.

Without the Telemedicine Licensure Compact, telehealth demand is restricted locally to the physician's home state. With the Compact, providers can serve more out-of-state customers remotely, and the expected profits r_t will increase. So, physicians become more likely to initiate telehealth services. Along with increased adoption, we expect to observe that physicians acquire more state licenses, increase service provision and receive more payments, as we will show in Table 2.

To illustrate the relevance of telehealth technologies, we utilize heterogeneity in the fixed cost C. If a physician's working hospital has implemented more telehealth infrastructure, then her initiation cost is lower since she does not need to purchase additional equipment. Besides, it is easier for her to learn from other telehealth providers in the same hospital. We will show that affected physicians with better hospital telehealth infrastructure will respond more heavily by acquiring more licenses and receiving more payments, in Table 3.

Lastly, we argue that wider adoption of telehealth services will change the competitive landscape, leading to different outcomes for rural and urban providers. In the U.S., most telehealth policies aim to improve healthcare services in rural areas. The Compact states that the "mission of the Compact is to increase access to health care – particularly for patients in underserved or rural areas." In addition, insurers often limit telehealth reimbursements only to rural patients. Medicare, which is our main source of payment data, requires that the originating sites be located in areas designated as a rural health profession shortage area or in counties not included in a metropolitan area. These policies essentially create a geographic supply-demand relationship: patients in rural areas demand telehealth services from providers in metro areas. On the one hand, urban providers are more likely to benefit financially from states joining the Compact. On the other hand, in-person services in rural hospitals will face new competition from distant metro counterparts via virtual services. We will illustrate the urban-rural differences in terms of financial impacts in Tables 4 and 5. In addition, we will evaluate the quality of care implications in Section 4.3.

3.4 Empirical Specification

Our identification strategy exploits the staggered entry of states into the Compact, thus we estimate a staggered difference-in-differences (DID) regression:

$$Y_{i,t} = \alpha + \beta Compact_{i,t} + \gamma Controls_{i,t} + \eta_t + \mu_i + \varepsilon_{i,t}. \tag{1}$$

Our analysis first focuses on the physician sample, which is a quarterly panel of doctors. In Equation (1), $Y_{i,t}$ is the outcome variable, measuring physician licenses, services and payments. $Compact_{i,t}$ is one if the physician's primary operating state participates in the Compact as of quarter t, and zero otherwise. Notice that for states joining the Compact before the actual operation, the variable becomes one only after 2017Q2.The coefficient of interest, β, estimates the relative effect of a state joining the Compact. We include physician fixed effects μ_i and year-quarter fixed effects η_t. This specification is the classic two-way fixed effect model for staggered treatments. We include two different batches of controls. The first group of controls includes physician-level variables. We include an indicator for whether the physician graduated more than 10 years ago, yet fewer than 25 years ago, as of quarter t ($MidSeniority_{i,t}$). Physicians in their early careers improve their quality of care through learning by doing. However, these learning effects stop later in their career. Note that, consistent with this expectation, Kane and Labianca (2011) show that information avoidance among doctors increases with age, and Tsugawa et al. (2017) find that patients treated by physicians older than 40 have a higher mortality than patients cared for by younger physicians. We also include an indicator for whether physician i has received disciplinary action from their medical board at any time up to and including quarter t ($PastAction_{i,t}$). The second group of controls accounts for the characteristics of the physician's hospital, including number of patients discharged in the previous year ($HosDischarge_{i,t-1}$), fraction of patients giving the highest overall ratings in the previous year ($HosRating_{i,t-1}$), and annual income (in millions) in the previous year ($HosIncome_{i,t-1}$). If a physician works for multiple hospitals, we aggregate the volume of discharges and income across all employing hospitals, and we take the average fraction of respondents indicating highest survey rating across employing hospitals.

We then conduct a hospital-level analysis, based on an annual panel of hospital level measures. The specification is similar to Equation (1), except that $Compact_{j,t}$ is defined for each hospital j in year t, and we include hospital fixed effects and year fixed effects. Similarly, the outcome variables $Y_{j,t}$, measure the hospital financial, operational and quality information. The control variables include hospital j's total income ($Income_{j,t-1}$), number of adult beds ($Bed_{j,t-1}$), number of employees ($PhyNum_{j,t-1}$), and number of inpatients discharged ($Discharge_{j,t-1}$), all in the previous year.

Finally, we conduct a county-level analysis, based on an annual panel of county level deaths by disease type. The specification is similar to Equation (1), except that $Compact_{k,t}$ is defined for each county k, in year t, and we include county fixed effects and year fixed effects.

4 Results

4.1 Telemedicine Licensure Compact Treatment Effect

Table 2 shows the average treatment effect of Compact entry. Column (1) confirms that physicians' number of active licenses rises with Compact entry, consistent with telehealth expansion. State licenses do not require quarterly renewal; rather, they typically remain valid for two to three years. The variable *LicenseNum* thus tends to follow a Poisson distribution, since it remains stable until the new application events arrive. In the rare case when a physician does not renew old licenses, this variable will also decrease. It is thus difficult to directly interpret the increase in new applications reflected in column (1). To ease interpretation and assess sensitivity to estimator choice, we also consider a Poisson model in Online Appendix Table A.2, where we show that the quarterly rate of new license applications increases significantly, by 9.4%, after Compact entry.

The remaining columns are consistent with increases in service amounts and revenues as a result of telehealth service expansion. In columns (2) through (4), we find that affected physicians provide significantly more Medicare services, treat more beneficiaries, and receive higher payments, by magnitudes ranging from 1.1% to 1.6%. Equivalently, these coefficients imply that an affected physician will serve 7.3 (1.4% $\times$ 522.6) more patients and receive \$2,132.2 (1.1% $\times$ \$193,835.9) more payments from Medicare, on average. Column (5) shows that the result is consistent if we use the standardized payment as our outcome variable. The CMS standardization process removes geographic differences in payment rates due to local wages, input prices, practice patterns, and beneficiary conditions.

Table 2: Telemedicine Licensure Compact Treatment Effect

This table shows the Telemedicine Licensure Compact treatment effect using Equation (1). $Compact_{i,t}$ is one if physician i's state has joined the Compact in time t, and zero otherwise. $LicenseNum_{i,t}$ is the number of active state licenses that physician i has in time t. $Log(MedService)_{i,t}$ is the logarithm of (one plus) the number of Medicare services delivered by physician i in year t. $Log(MedBenes)_{i,t}$ is the logarithm of (one plus) the number of Medicare beneficiaries receiving physician i's services in year t. $Log(MedPay)_{i,t}$ is the logarithm of (one plus) Medicare payment after applying deductible and coinsurance amounts for provider i's services in year t. $Log(MedStdPay)_{i,t}$ is the logarithm of (one plus) Medicare payment after applying deductible and coinsurance amounts, and geographic standardization for provider i's services in year t. The coefficients of control variables are omitted to save space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, Medicare utilization information at an annual frequency. Thus, a year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and a year fixed effect *Year FE* is included for the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	0.015***	0.016***	0.014***	0.011***	0.010***
	(5.823)	(3.544)	(4.613)	(2.848)	(2.659)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.79	0.87	0.88	0.87	0.89

The DID specification is only valid if the parallel trend assumption is satisfied. In a staggered treatment setting, we assess this by plotting dynamic coefficients across time periods relative to the timing of treatment, as in Autor (2003). Specifically, we estimate

$$Y_{i,t} = \alpha + \sum_{s=-l}^{-2} \beta_s Compact_{i,t}^{s} + \sum_{s=0}^{h} \beta_s Compact_{i,t}^{s} + \gamma Controls_{i,t} + \eta_t + \mu_i + \varepsilon_{i,t}. \qquad (2)$$

In Equation (2), $Compact_{i,t}^{s}$ is one if physician i's state had joined Compact as of time $t - s$, and zero otherwise. In the licensure sample, for example, $Compact_{i,t}^{-3}$ equals one for the quarter t that is three quarters before the state entry quarter. The interpretation of β_s is the relative difference between the treatment and control groups s periods after the treatment. For boundary periods $s = -l$ and $s = h$, the dummies represent l periods or more before and h periods or more after the shock, respectively. We drop the coefficient for $s = -1$, which serves as the reference period, i.e., the benchmark difference. Figure 2(a) confirms that all the coefficients in the leading periods ($s \leq -2$) show no statistically significant trends, and are close to zero for $LicenseNum$. Meanwhile, the treatment effects in the lagging periods are apparent. We obtain similar patterns if we plot the coefficients dynamics for the remaining variables in Table 2 for robustness. However, since the Medicare utilization data are aggregated yearly, there are only two treatment periods (years) after the shock (2017 and 2018).

We also utilize the gap between state adoption (as early as 2015Q2) and the Telemedicine Compact operation (2017Q2) as a placebo test. If some omitted variables simultaneously lead to state participation and generate the above effects, then we should observe treatment effects in 2015 and 2016 for states joining before the actual operation. Online Appendix Figure A.1 plots the treatment effects only for these early-adopting states (who joined by 2016Q4) over calendar time. All coefficients between these states' announcement of their intent to enter the Compact, and the actual implementation of the Compact, are statistically insignificant. Again, the absence of an effect for these early-announcer states in the periods leading up to the Compact's first implementation is consistent with the idea that states' Compact entry timing is plausibly exogenous.

To further highlight that the impact of Compact entry is directly associated with telehealth adoption, we next consider heterogeneity in the telehealth readiness of physicians' working hospitals. If the physician's workplace has better telehealth infrastructures, then she has a lower fixed cost of adopting and learning new technologies. We create the measure $TeleScore_{i,t-1}$ based on the AHA healthcare IT survey, which is a voluntary survey taken by a subgroup of Medicare hospitals. There are three survey questions related to telehealth services, including telehealth implementation, remote monitoring, and mobile device usage. Each question is rated by six scales, from the worst case, "Not in Place and Not Considering Implementing", to the best case, "Fully Implemented Across All Units." We then convert these scales to numeric scores ranging from one (worst) to six (best), and take the average across all answered questions to generate $TeleScore_{i,t-1}$.

We add an interaction term between $Compact_{i,t}$ and $TeleScore_{i,t-1}$ in column (1) of Table 3. For all outcome variables, interaction coefficients are positive and significant, suggesting relatively larger positive effects in the presence of better telehealth infrastructure. Moreover, the coefficients of $Compact_{i,t}$ become significantly negative, implying losses for treated providers who lack telehealth infrastructure. For example, column (4) implies that an affected physician in a working hospital that has no intentions to implement any telehealth services, i.e. $TeleScore_{i,t-1} = 1$, will see significant declines in Medicare payments annually, of roughly 3.1% ($-4.2\% + 1.1\%$). This implies that telehealth readiness is a necessary condition for physicians to take advantage of the Compact.

Next, we consider physician locations within a state, in terms of their proximity to a state border. If the main purpose of applying for additional licenses was to operate in person, in neighboring states *physically*, then affected physicians located on state borders should exhibit a larger response to Compact entry, applying for more licenses and earning more revenues

Figure 2: Telemedicine Licensure Compact Treatment Effect: Coefficient Dynamics

This figure plots the coefficient dynamics of Telemedicine Licensure Compact treatment effects, defined in Equation (2). Each coefficient represents the relative difference between the treatment and control group s periods before or after the participation quarter, relative to the omitted reference period, i.e., the period before participation ($s = -1$). For boundary periods, the dummies represent l periods or more before and h periods or more after the shock, respectively. 95% confidence intervals are indicated by the solid lines. Figure titles indicate the outcome variables corresponding to Table 2.

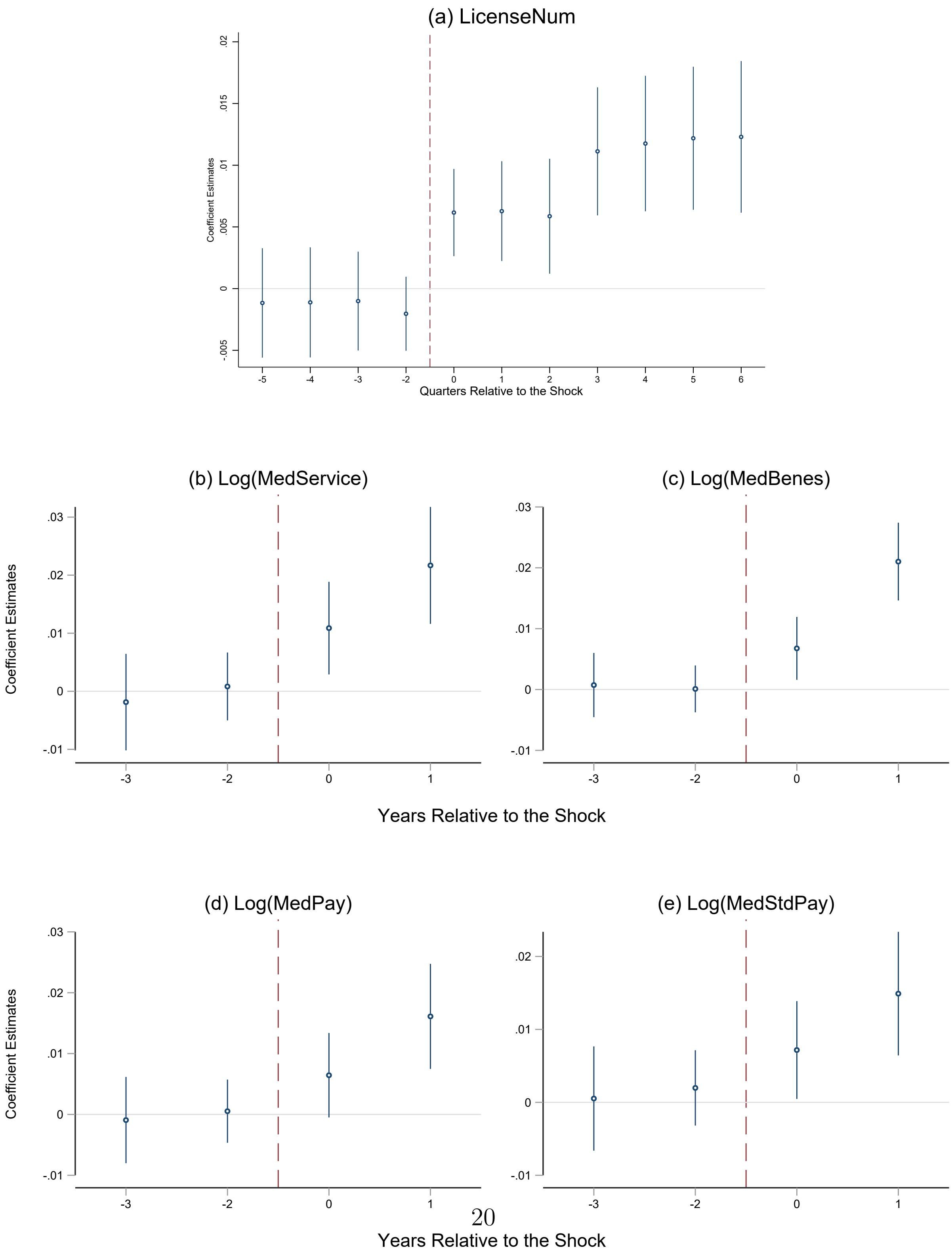


Table 3: Telemedicine Licensure Compact Treatment Effect and Telehealth Readiness

This table shows the heterogeneous effects of Telemedicine Licensure Compact entry, with respect to telehealth readiness. $TeleScore_{i,t-1}$ is the telehealth readiness score of physician i's working hospital in the year before time t. $Compact_{i,t}$, and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted to save space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, Medicare utilization information at an annual frequency. Thus, a year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and a year fixed effect *Year FE* is included in the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	−0.021**	−0.037*	−0.042***	−0.042**	−0.036*
	(−2.257)	(−1.720)	(−2.975)	(−2.195)	(−1.955)
$TeleScore_{i,t-1} \times Compact_{i,t}$	0.007***	0.010**	0.011***	0.011***	0.009**
	(3.907)	(2.356)	(3.739)	(2.730)	(2.520)
$TeleScore_{i,t-1}$	−0.001	0.004***	0.002***	0.002**	0.001
	(−1.433)	(3.909)	(2.866)	(2.476)	(1.391)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	1,493,061	427,381	427,381	427,381	340,894
adj. R^2	0.82	0.89	0.89	0.88	0.90

(given they would benefit from lower travel costs than physicians residing in the middle of a state). Online Appendix Table A.3 rules this explanation out via an additional interaction term, based on whether a physician's workplace is in a border county. Affected physicians on state borders do not appear to apply for new licenses any more frequently, and surprisingly they tend to *lose* payments. These results are consistent with local customers on state borders switching to more distant providers, via telehealth.

Collectively, our results show that the introduction of the Telemedicine Licensure Compact motivates physicians to apply for additional licenses, to gain access to a broader market through telehealth services. We also have shown that only physicians with the resources and infrastructure to supply telehealth services can financially benefit. This heterogeneity foreshadows our findings around urban-rural differences, that telehealth adoptions significantly change the competitive landscape.

4.2 Geographic Inequalities

We also hypothesize that in-person rural services will face new competition from distant metro providers, following the expansion of telehealth services. Accordingly, we expect that license application and financial effects would run in opposite directions for providers in urban versus rural areas. In Table 4 we evaluate this prediction; we add an interaction term, multiplying $Compact_{i,t}$ with $Metro_i$, which is one if physician i's working hospital is in a metropolitan area (USDA rural-urban commuting area code is smaller than or equal to three). Column (1) shows that affected rural physicians do not change their license application frequency to a statistically significant degree, whereas urban providers react

Table 4: Telemedicine Licensure Compact Treatment Effect and Urban-Rural Differences

This table shows the heterogeneous effects of Telemedicine Licensure Compact entry across urban and rural locations. $Metro_i$ is one if physician i is located in a metropolitan area, and zero otherwise. There exist no physicians whose $Metro_i$ changed in our sample period, so the coefficient of $Metro_i$ is not identified given the *Physician FE*. $Compact_{i,t}$ and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted to save space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, Medicare utilization information at an annual frequency. Thus, a year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and a year fixed effect *Year FE* is included in the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	−0.009	−0.053***	−0.031***	−0.056***	−0.051***
	(−1.271)	(−3.662)	(−3.268)	(−4.362)	(−4.146)
$Metro_i \times Compact_{i,t}$	0.027***	0.077***	0.049***	0.075***	0.068***
	(3.558)	(5.182)	(5.103)	(5.670)	(5.374)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.79	0.87	0.88	0.87	0.89

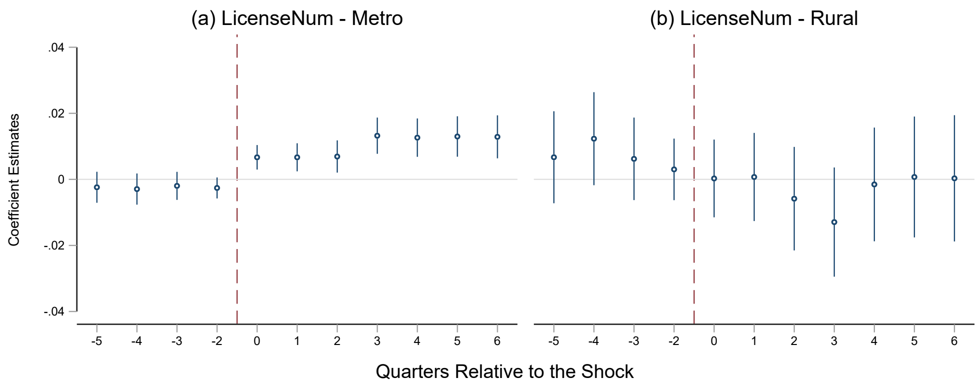
strongly, exhibiting a 2.7% rise in licensure. The different treatment effects are illustrated directly in Figure 3, where we separately plot the coefficient dynamics for urban and rural physicians.

The remaining columns in Table 4 show that treated rural physicians suffer financially too, as their service amounts and payments from Medicare systematically drop, by an estimated 3.1% and 5.6%, respectively, as indicated by the coefficients associated with $Compact_{i,t}$. Only urban providers truly benefit. For example, column (4) shows that their Medicare payments increase by 1.9% (−5.6% + 7.5%). In sum, while Table 2 demonstrates that the average treatment effects when pooling urban and rural physicians together suggests broad benefits at first glance, breaking them apart yields stark differences, suggesting shifts from rural in-person services to urban telehealth services.

Thus far, we have shown evidence of geographic inequalities based on Medicare services and payments received at the physician level. However, these measures reflect only part of the activity in which the physicians are engaged, because there are non-Medicare reimbursements from other insurers to consider. Accordingly, to provide a complete picture of revenue effects, we next investigate hospital-level outcomes, in Table 5. If our hypothesized competition effect exists, then we would expect to obtain similar results in terms of revenues and patient flows aggregated to the hospital level. This is precisely what we observe. Column (1) shows that the affected rural hospitals experience a 4.6% decline in total revenue, whereas their urban counterparts experience a gain of 2.6% (−4.6% + 7.2%). The result is consistent if we use net revenues as our outcome variable, which represents the actual payments from insurers to providers after contractual adjustments. We also document that patient volumes are affected differently between urban and rural areas, in column (3). Our estimates are

Figure 3: Urban-Rural Differences in Coefficient Dynamics

This figure plots the coefficient dynamics associated with the Telemedicine Licensure Compact treatment, separated by urban and rural areas. To generate figures (a) and (b), we separately estimate Equation (2) in the urban and rural sample of physicians. Each coefficient represents the relative difference between the treatment and control group s quarters before or after the participation quarter. All coefficient estimates are relative to the difference in the quarter before participation ($s = -1$). For boundary periods, the dummies represent l quarters or more before and h quarters or more after the shock, respectively. 95% confidence intervals are indicated by the solid lines.



consistent with the idea that rural inpatients shift to become urban outpatients, serviced via telehealth channels. Lastly, we find that the average employee salary in affected rural hospitals significantly decreases, while that in metro hospitals increases, consistent with our earlier Medicare payment result. This is somewhat expected, because the common healthcare compensation model follows a fee-for-service approach. Accordingly, physician salaries are a function of the number of services they render.

In summation, we find that telehealth expansion leads to clear winners and losers, in terms of financial implications. Urban providers financially benefit, both because they tend to have better telehealth infrastructure, and because they are sought after by rural patients, due to their better quality of care. Our estimates are broadly consistent with a substitution effect (Ayabakan et al., 2020), with rural inpatients transitioning to become urban (telehealth-mediated) outpatients. In addition, our estimates suggest a possible gateway effect (Bavafa et al., 2018), wherein rural patients may follow up on their initial telehealth visits by seeking inpatient treatment at their new providers' urban locations. This increase in market concentration is important. The healthcare literature documents that market consolidations give hospitals more bargaining power with insurers, which in turn increases service prices (e.g. Gaynor et al., 2015). Our findings note a novel mechanism by which such market powers may arise, beyond mergers (Dafny et al., 2019; Lewis and Pflum, 2015); we show that a similar dynamic may also arise due to telehealth service expansion.

Table 5: Urban-Rural Differences in the Treatment Effects at the Hospital Level

This table shows the heterogeneous Telemedicine Licensure Compact treatment effects based on urban-rural location, at the hospital level. The panel unit is a hospital, observed yearly. $Compact_{j,t}$ is one if hospital j's state has joined the Compact as of time t, and zero otherwise. $Metro_j$ is one if hospital j is located in a metropolitan area, and zero otherwise. There exists no hospital whose $Metro_j$ changes during our sample period, so the coefficient of $Metro_j$ is not identified in the presence of the *Hospital FE*. $Log(Rev)_{j,t}$ is the logarithm of (one plus) hospital j's total revenues in year t. $Log(NetRev)_{j,t}$ is the logarithm of (one plus) hospital j's net revenues after insurers adjust for contractual allowances in year t. $Log(Patient)_{j,t}$ is the logarithm of (one plus) hospital j's discharged patient volume in year t. $Log(Salary)_{j,t}$ is the logarithm of (one plus) hospital j's average employee salary in year t. The coefficients of control variables are omitted to save space. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Log(Rev)*	(2) *Log(NetRev)*	(3) *Log(Patient)*	(4) *Log(Salary)*
$Compact_{j,t}$	−0.046**	−0.025	−0.032***	−0.030***
	(−2.158)	(−1.234)	(−3.237)	(−7.592)
$Metro_j \times Compact_{j,t}$	0.072***	0.042**	0.071***	0.042***
	(3.274)	(2.041)	(6.419)	(7.658)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
N	26,969	26,956	26,950	27,302
adj. R^2	0.98	0.97	0.99	0.91

4.3 Quality Implications

Having considered the financial implications of telehealth expansion, we next consider the effects on healthcare quality. The first question we address here is whether better physicians are more likely to apply for interstate licenses (engage in telehealth delivery) following states' entry into the Compact. Measuring physician skills is not easy, e.g., there is mixed evidence on whether online physician ratings are informative about actual service quality (Lu and Rui, 2018; Saifee et al., 2020; Gao et al., 2015). With these difficulties in mind, we combine both off-line and online measures to operationalize physician quality. First, we obtain records of medical boards' disciplinary actions against physicians from docinfo.org. These records reflect punitive actions against providers in response to unprofessional, incompetent, or improper medical practices, including drug abuse and off-label prescription. As such, having disciplinary actions indicates on one's record is an objective indication of low quality. To alleviate the concern that physician quality endogenously changes after the shock, we calculate a snapshot value of whether a physician has received disciplinary action, $PastAction_{i,\tau}$ for the treatment group, as of the period before their state's Compact entry (denoted by τ). For the control group, the interaction term is zero. Second, we collect online ratings for physicians from healthgrades.com, captured by $PhyRating_i$. The healthgrades.com website uses a five-star rating system, and we collect a snapshot value of the average historical ratings for physicians as of November 2020.

Table 6 shows consistent evidence that physicians of higher quality tend to be more responsive to the shock. For example, physicians having warnings from their medical board *prior* to the shock are 4.9% less likely to apply for additional licenses. Further, their Medi-

Table 6: Telemedicine Licensure Compact Treatment Effect and Physician Quality

This table shows the heterogeneous Telemedicine Licensure Compact treatment effects depending on physician quality. In Panel A, $PastAction_{i,\tau}$ is one if physician i had received a disciplinary action from their medical board as of the period of their state's Compact entry (denoted by τ), and zero otherwise. In Panel B, $PhyRating_i$ is the online physician rating from healthgrades.com, ranging from one to five. We drop physicians who have no online ratings. Both $PastAction_{i,\tau}$ and $PhyRating_i$ are time invariant for a given physician i, thus the coefficients of their main effects are not identified in the presence of a *Physician FE*. $Compact_{i,t}$ and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted to save space. *Physician FE* is the physician fixed effect. The licensure information is available on a quarterly basis, and Medicare utilization information on an annual basis. As such, a year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and a year fixed effect *Year FE* is included in the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Past Medical Board Actions

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	0.016***	0.017***	0.014***	0.012***	0.011***
	(5.959)	(3.705)	(4.735)	(2.990)	(2.785)
$PastAction_{i,\tau} \times Compact_{i,t}$	−0.049*	−0.091**	−0.047**	−0.068**	−0.058*
	(−1.742)	(−2.390)	(−2.140)	(−2.075)	(−1.763)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.79	0.87	0.88	0.87	0.89

Panel B: Online Rating

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	−0.140***	−0.121***	−0.118***	−0.165***	−0.148***
	(−5.305)	(−2.714)	(−4.506)	(−4.603)	(−4.351)
$PhyRating_i \times Compact_{i,t}$	0.041***	0.031***	0.032***	0.043***	0.038***
	(6.404)	(2.912)	(4.985)	(4.912)	(4.616)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	635,610	167,483	167,483	167,483	141,195
adj. R^2	0.80	0.88	0.88	0.86	0.87

care service volumes reduce by an estimated 9.1%, implying payment losses. In other words, poor-quality physicians tend to lose their customers following states' entry into the Compact, perhaps because telehealth services enable patients to switch to better, more distant providers.

While the above findings demonstrate that physicians are higher quality, *ex ante*, are more likely to engage in telehealth delivery, it is not clear whether those physicians are able to maintain delivery quality following that transition, given it entails increased service volume and a new, digital medium. We thus explore patient-related measures of quality in Table 7, including patient satisfaction and health outcomes at the hospital level. The first row shows that patients become slightly more satisfied with treated hospitals in rural regions following Compact entry, though the effects are small and insignificant. Investigating the effects on pneumonia mortality and readmission incidence, we find that rural hospitals exhibit significant reductions in their yearly number of readmitted patients (0.64) and patient deaths (1.24). Aggregated across all 2,487 treated hospitals, nationally, the latter estimate

Table 7: Telemedicine Licensure Compact Quality Impacts at the Hospital Level

This table shows the Telemedicine Licensure Compact impact on patient quality of care at the hospital level. The panel unit is a hospital, observed annually. $Overall_{j,t}$, $Recommend_{j,t}$, $Helpful_{j,t}$ and $Info_{j,t}$ capture the percentage of patients that give the highest rating for hospital j's services in year t, in terms of overall performance, willingness to recommend, staff helpfulness, and recovery information, respectively. $PNReadm_{j,t}$ and $PNMort_{j,t}$ are the number of 30-day unplanned readmissions and instances of mortality for hospital i's pneumonia patients, in year t. $Compact_{j,t}$ is one if hospital j's state has joined the Compact in time t, and zero otherwise. $Metro_j$ is one if hospital j is located in a metropolitan area, and zero otherwise. No hospital exhibits a change in $Metro_j$ during the sample period, thus the coefficient for $Metro_j$'s main effect is not identified in the presence of the *Hospital FE*. The coefficients of control variables are omitted to save space. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) ***Overall***	(2) ***Recommend***	(3) ***Helpful***	(4) ***Info***	(5) ***PNReadm***	(6) ***PNMort***
$Compact_{j,t}$	0.082	0.355	0.272	0.080	−0.635***	−1.242***
	(0.381)	(1.592)	(1.159)	(0.572)	(−7.854)	(−16.100)
$Metro_j \times Compact_{j,t}$	−0.668***	−0.797***	−0.835***	−0.460***	0.727***	1.469***
	(−2.667)	(−3.192)	(−3.182)	(−2.988)	(5.962)	(11.877)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
N	19,970	19,966	15,893	19,968	18,962	18,908
adj. R^2	0.80	0.83	0.54	0.76	0.98	0.97

translates to roughly 3,000 fewer deaths annually.

We find opposing effects when it comes to the quality of care received by urban inpatients. The overall satisfaction level and the willingness to recommend significantly reduce among urban inpatients following states' entry into the Compact. In addition, there is not significant improvement in pneumonia treatment. For example, pneumonia death for urban hospitals slightly increases, by 0.227 ($-1.242 + 1.469$). Our results thus hint at a welfare trade-off that was first proposed by Rajan et al. (2019): telehealth adoption increases *total* welfare by enabling medical service delivery to a larger group of patients. However, this is not a Pareto improvement. The patients who live close to the telehealth provider and therefore only visit in person can be burdened by increased congestion and reduced service times.

One may argue that the results in Table 7 are limited to the group of patients who continue to employ in-person rural services after the shock, and those patients may be different in some way. To evaluate this possibility, we conduct a more comprehensive analysis, considering the aggregated deaths due to chronic disease at the county level. Further, we collect data on yearly deaths due to acute myocardial infarction, Alzheimer's disease, chronic kidney disease, chronic obstructive pulmonary disease, cancer, diabetes, and heart failure for 1,405 counties between 2013 to 2018. These 1,405 counties are those that report the mortality data in question to CDC WONDER without any missingness. These counties represent around half of all 3,006 U.S. counties. In Table 8, we see that for six out of the seven diseases mentioned, treated rural counties experienced substantial reductions in the number of deaths, with magnitudes ranging from 8.1% to 15.5%. However, the positive and significant coefficients associated with the interaction terms imply that urban treated

Table 8: Telemedicine Licensure Compact Impacts on Quality at the County Level

This table shows the effect of Telemedicine Licensure Compact entry on quality of care at the county level. Each observation captures information for county k in year t. The outcome variables include the logarithm of (one plus) number of deaths for acute myocardial infarction ($log(AMI_{k,t})$), Alzheimer's disease ($log(Alzheimer_{k,t})$), chronic kidney diseases ($log(CKD_{k,t})$), chronic obstructive pulmonary disease ($log(COPD_{k,t})$), cancer ($log(Cancer_{k,t})$), diabetes ($log(Diabetes_{k,t})$), and heart failure ($log(HF_{k,t})$). Control variables include county k's population, unemployment rate, and natural deaths, all in the previous year $t-1$. The coefficients of control variables are omitted to save space. Year and county fixed effects are included, as indicated. Standard errors are clustered at the county level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) *Log(AMI)*	(2) *Log(Alzheimer)*	(3) *Log(CKD)*	(4) *Log(COPD)*	(5) *Log(Cancer)*	(6) *Log(Diabetes)*	(7) *Log(HF)*
$Compact_{k,t}$	−0.081*	−0.151***	−0.101**	−0.144**	−0.105*	−0.155**	-0.006
	(−1.941)	(−2.667)	(−1.988)	(−2.131)	(−1.835)	(−2.452)	(−0.085)
$Metro_k \times Compact_{k,t}$	0.084	0.206***	0.202***	0.035	0.123*	0.176**	0.041
	(1.402)	(3.128)	(3.422)	(0.475)	(1.907)	(2.532)	(0.519)
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
N	8,430	8,430	8,430	8,430	8,430	8,430	8,430
adj. R^2	0.89	0.92	0.91	0.88	0.91	0.90	0.88

counties experience no improvements, and in some cases they even deteriorate.

What generates these rural improvements? There are several possible mechanisms. First, rural hospitals may be over-utilized and lack resources prior to Compact entry. Accordingly, the decline in patient inflows may lead to greater slack resources. Indeed, in Online Appendix Table A.4 we show that, after a host state enters the Compact, the discharge rate per bed and the bed utilization of rural hospitals both decrease significantly. Given the reduced patient load, rural providers may be able to provide better care and attention. Second, rural inpatients may consult urban specialists about their conditions through video conferences and remote monitoring, and receive better care management. Finally, seeing declines in their revenue, rural hospitals may increase their effort in the interests of competition and survival.

5 Robustness Checks

In this section, we provide a few robustness checks for our results related to urban-rural differences in telehealth effects. First, there is a possible concern that our results are driven by unobservable state-level conditions, such as state policies (e.g. Medicaid expansions) or market consolidation (local acquisitions or bankruptcies). These omitted variables may simultaneously drive states' entry into the Compact and enlarge the financial disparities between urban and rural providers. One solution to this endogeneity concern is to replace the time fixed effects with state-time fixed effects, which will absorb all time-varying state characteristics. Note that, because Compact entry is a state-level variable, such a specification only allows for identification of the coefficient associated with $Metro_i \times Compact_{i,t}$. We report the results of this estimation in Online Appendix Table A.5. These results reflect a within-state comparison; that is, the effects of Compact entry on the relative performance of urban and rural providers in terms of financial and quality of care outcomes, in the *same* state. All of the results are consistent with earlier findings.

It is worth pointing out that the above within-state urban-rural disparities may be driven in part by *interstate* substitution and competition. Indeed, facilitating inter-state telehealth delivery is a key objective of the Compact. For example, both Minnesota and Wisconsin decided to participate in the Compact early on. After joining the Compact, an urban Minnesotan hospital may financially benefit by serving rural Wisconsinites through telehealth. Similarly, rural Minnesotan patients can now enjoy telehealth services from Wisconsin-based providers.

We next consider a more granular healthcare market definition, drawing on the Hospital Referral Regions (HRRs) developed by the Dartmouth Atlas of Health Care. An HRR is a group of communities, identified on the basis of referral patterns for tertiary care for Medicare beneficiaries, focusing on referrals for major cardiovascular surgical procedures and neurosurgery. In Online Appendix Table A.6, we replace the time fixed effects with HRR-time fixed effects, which will absorb all time-varying, local healthcare market characteristics. Since HRRs often combine communities across state borders, the coefficients of $Compact_{i,t}$ remain identified in this regression. Once again, the results are consistent with earlier findings.

Next, we consider variation in the effects based on patients' quality of internet access. For rural patients to utilize telehealth services, a prerequisite is that they must have access to high-speed internet, to connect with providers. Therefore, rural affected physicians who are based in regions with poor internet infrastructure should be relatively protected from urban competition through telehealth. Thus, if the mechanism is what we believe, these providers should not exhibit revenue losses following a state's compact entry. To evaluate this, we draw on the Federal Communications Commission (FCC) broadband coverage annual report, from June 2016 to 2018. For each county, the FCC report documents the percentage of rural residents that have zero broadband internet service providers, where broadband is defined as a minimum of 25 Mbps download speed and 3 Mbps upload speed. We create a measure based on the average percentage of rural population lacking access to such services between 2016 and 2018. This measure, *PoorInt*, equals one if the average percentage is greater than the 90^{th} percentile among all counties. This cutoff indicates that 62% of the rural population has no access to broadband. Even though the *PoorInt* indicator increases with rurality, Online Appendix Table A.7 shows that the coefficients of $PoorInt_i \times Compact_{i,t}$ are significantly positive for all Medicare utilization variables. This result is consistent with our expectation; affected physicians in rural counties that lack broadband internet access do not suffer financially from telehealth competition.

Table 4 draws on the Medicare data to evaluate urban-rural differences in financial benefits, this time at the physician level. The outcome measure we employ here captures physician promotion payments documented in the Open Payment Database. Our expectation is that drug companies will find it more profitable to promote drugs through affected physicians, as they become able to serve out-of-state patients through telehealth, because those physicians gain a larger market scope. Column (1) in the Online Appendix A.8 confirms this hypothesis, showing that affected physicians receive 1.6% more promotion payments every quarter after the shock. Considering urban-rural differences, we again see that this average masks a combination of rural losses and urban gains. Affected rural physicians lose 12.3% of compensation and those in urban areas benefit from a 15.6% increase.

Our main specification is a staggered DID model with two-way fixed effects. Recent literature shows that with varied treatment timings, the estimated DID coefficient is a weighted average of many simple DID effects across different treatment groups (e.g. **?**). To ensure that our results are not driven by a particular treatment event in the panel, we adopt a simple method in Online Appendix Table A.9. We define the variable $Compact^{s}_{i,t}$ which indicates if physician i's state has joined the Compact by time t *and*, and the joining year is s.[16] In other words, the coefficient associated with $Compact^{2015}_{j,t}$, for instance, represents the effect of entry for the group of states that joined in 2015. We interact these variables with metropolitan indicators. Upon separating the DD estimations between the different entry cohorts, our results remain broadly consistent across each of them. Most importantly, the interaction terms are positively significant in almost all cohorts for main outcome variables.

Lastly, we explore controlling for the other interstate licensure compacts. The Nursing Licensure Compact (NLC) was originally formed on January 10, 2000, and most participating states joined in the early 2000s. Given the emerging need for telehealth services, the enhanced Nurse Licensure Compact (eNLC) was introduced on January 19, 2018, with 34 current member states. The Physical Therapy Licensure Compact (PTLC) was officially enacted on April 25, 2017, with 29 current member states. The present study has focused on the Telemedicine Licensure Compact for the following reasons. First, our individual-level information pertains to physicians; we do not have individual-level licensure and payment data for nurses or physical therapists. Second, we expect a larger effect from the physician compact, because of physicians' (in particular specialists') greater demand from patients. That said, we can still evaluate urban-rural differences in response to *any* Compact membership, focusing on hospital financial information, assuming that the effects from different compacts will aggregate consistently at the hospital level. In Online Appendix Table A.10,

[16] Since the 2018 cohort is too small compared to the others, we have three groups (2015, 2016, and 2017) by grouping 2017 and 2018 together. Besides, $Compact^{s}_{i,t}$ can become one only after the actual Compact operation in 2017.

we define a new treatment variable, $AllCompact_{j,t}$, to indicate whether the state has joined any of these compacts as of period t. We document consistent results around urban-rural differences at the hospital level.

6 Discussion

We have presented a novel, large-scale empirical study of the effects that telehealth technologies may have on competition between urban and rural healthcare providers. We consider the timing of states' entry into the Telemedicine Licensure Compact, which reduces the time and effort necessary for physicians' to engage in the delivery of interstate telehealth services. Taking this entry event as an exogenous shock to the number of physicians engaging in telehealth in a particular geography, we estimate the effect of telehealth expansion on financial and healthcare quality outcomes for different segments of providers and patients. We provide causal evidence that telehealth expansion leads to a systematic shift in patient-provider interactions, consistent with the notion that many rural inpatients become urban outpatients. Though we observe an associated reallocation of revenues from rural to urban providers, we also observe slight (albeit statistically insignificant) increases in the satisfaction of rural inpatients, as well as significant declines in rural patient readmission and mortality among patients suffering from chronic diseases.

Our work makes a number of notable contributions. We build most directly on the prior theoretical work by Rajan et al. (2013) and Rajan et al. (2019). Our empirical results confirm some of these prior theoretical findings, namely that urban providers benefit financially, generally. More broadly, our results demonstrate that technological innovations may make it increasingly difficult for rural providers to compete. Better computers, broadband Internet penetration, video conferencing technologies, and wearable devices reduce patient and provider setup costs, as well as the need for follow-up visits. Additionally, many states have recently passed telehealth parity laws, requiring insurance providers to reimburse for services in the same manner, whether delivered digitally or in person. Absent policy intervention, the urban-rural disparity in health provider financial performance is likely to grow. Our work complements Rajan et al. (2013) with additional quality of care insights. The quality reduction for the urban treatment group may be due to a reduced service time and longer waiting for existing patients, discussed in Rajan et al. (2019).

Our work also suggests at least two important questions that hospital administrators and policymakers may need to address in the coming years. First, a pressing question is how urban providers can ensure inpatient quality of care is sustained, as their attention shifts toward digitally-mediated outpatient services? Recent technological developments in large hospitals, spurred by the COVID-19 pandemic, point to possible paths forward for increased flexibility and performance. Recent reports indicate that many large hospitals have recently introduced inpatient telemedicine platforms, turning rooms and wings into isolation units for infected patients, complete with connected devices and A/V systems that allowed nearby nurses and physicians to monitor patients from elsewhere in the hospital. These advancements mean that many hospitals have instituted systems that enable more efficient care of larger volumes of inpatients. The advancement in hospital technologies and infrastructure also creates the opportunity for hospitals to assemble geographically dispersed, virtual personal care teams for patients.

Second, given our finding that rural hospitals largely lose out to their urban counterparts, another natural question that arises is whether and how rural hospitals might survive in the long term. Although rural hospitals draw small revenue from serving as an access point for telehealth services, even that revenue source is set to dwindle in the coming years as the quality of rural home internet access and technology continues to improve. Although our findings indicate short-run benefits for inpatient satisfaction and the quality of inpatient care, our results cannot speak to whether that is a short-run benefit of slack resources, or due to a competitive response on the part of rural providers. To the extent rural provider revenues will erode under telehealth, the long-run sustainability of rural communities' hospitals will be called into question. This is problematic, given rural hospitals provide necessary emergent care to rural populations, in addition to serving as a large employer.[17] One option that has seen some success is for rural communities themselves to acquire ownership of the hospital, and to subsidize operations through additional taxation.[18]

7 Limitations & Conclusion

Our work is subject to a number of limitations. First, we are unable to evaluate all of the mechanisms behind the improvements in rural patient health outcomes. As noted earlier, it may be the case that rural providers benefit from greater slack resources as their inpatients shift to urban telehealth providers. Alternatively, rural providers may have responded to the threat of competition by investing in their service delivery. In reality, both mechanisms may be at play. Future work can seek to examine these competitive responses more closely.

Second, although our work provides a broad consideration of telehealth expansion and its implications for healthcare competition across the urban-rural divide, our analyses do

[17] The presence of a hospital is crucial to attracting young professional residents, as well as industrial manufacturers.

[18] Many rural hospitals have survived by merging with larger health systems, or consolidating a variety of community services under one roof.

not account for the recent growth of direct to consumer (D2C) telehealth offerings (Jain et al., 2019). Many digital services have been offering online prescriptions for a number of years now, e.g., contraception, erectile dysfunction, hair loss. More recently, however, purely digital platforms like Teladoc and AmWell have begun to offer a wider range of direct to consumer medical services, absent the involvement of hospitals or clinics, and some of these services are also integrated with retail pharmacy networks such as CVS and Walgreens, to provide brick-and-mortar points of access. These developments imply significant disruption may be on the horizon for traditional medical providers, urban and rural alike. Future work might consider the expansion of D2C telehealth offerings, to understand the effect these entrants are having on incumbent providers.

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Online Appendix for "Healthcare across Boundaries: Urban-Rural Differences in the Financial and Healthcare Consequences of Telehealth Adoption"

[Online Supplementary Material]

Table A.1: State Summary Statistics Before Shocks

This table provides the ex ante state characteristics in 2014 among the treatment and control groups. $West$, $South$, $Northeast$ and $Midwest$ denote the Census Bureau-designated four statistical regions. For each state, one of these variables is one and zero for the other three. $Medicaid$ is one if the state expanded Medicaid coverage for most low-income adults to 138% in 2014, and zero otherwise. *Legis_Rep* is one if the republican party holds both state chambers, i.e. has the state legislative control, in 2014, and zero otherwise. *Gov_Rep* is one if the state governor is republican, and zero otherwise. $PersonInc$ is the state's 2014 personal income per capita. $Genhlth$ is the 2014 average general health rating across the state's BRFSS respondents. $Phyhlth$ and $Menhlth$ are the 2014 average number of days in a month during which the state's BRFSS respondents believe their physician and mental conditions are not good, respectively. Column (1) shows the average across non-Compact states and column (2) shows that of the member states. Column (3) shows the difference in mean, with t-statistics in the parenthesis. Column (4) shows the p-values of the difference. Column (5) estimates a Cox Proportional-Hazards model for the timing of joining Compact. In this model, the "failure" denotes state's participation in the Compact, and survival time is the number of years from 2014 to the time a state joined compact (if they ever do), or to 2020. $Midwest$ is dropped in the Cox model due to multicollinearity. t-statistics are in the parenthesis.

	(1)	(2)	(3)	(4)	(5)
	Mean				
	Control	***Treated***	***Difference***	***p-value***	***Cox***
West	0.24	0.27	−0.03	0.82	−0.051
			(−0.25)		(−0.091)
South	0.38	0.30	0.08	0.56	−0.662
			(0.60)		(−1.177)
Northeast	0.24	0.13	0.11	0.34	−0.328
			(0.95)		(−0.404)
Midwest	0.14	0.30	−0.16	0.20	0.000
			(−1.30)		(.)
Medicaid	0.57	0.47	0.11	0.47	−0.614
			(0.75)		(−1.203)
Legis_Rep	0.52	0.55	−0.03	0.85	−0.612
			(−0.20)		(−1.106)
Gov_Rep	0.48	0.62	−0.14	0.32	0.356
			(−1.00)		(0.732)
PersonInc	48,298.62	46,617.27	1,681.35	0.47	−0.000
			(0.75)		(−1.367)
Genhlth	2.47	2.45	0.01	0.73	−1.638
			(0.35)		(−0.556)
Phyhlth	3.87	3.77	0.10	0.63	0.197
			(0.50)		(0.352)
Menhlth	3.54	3.33	0.21	0.17	−0.579
			(1.40)		(−0.963)

Table A.2: Poisson Model of Application

This table estimates a Poisson arrival model of applying new licenses following the shock. $ApplyCount_{i,t}$ is the number of unique states licenses that physician i has applied for by quarter t. $ApplyCount_{i,t}$ is different from $LisenseNum_{i,t}$ because the latter only counts the number of *active* state licenses that physician i has in quarter t. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. *Yr-Qtr FE* is the year-quarter fixed effect. Standard errors are clustered at the physician level and z-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	ApplyCount	***ApplyCount***	***ApplyCount***	***ApplyCount***	***ApplyCount***
$Compact_{i,t}$	0.094***	0.053***	0.107***	0.093***	0.093***
	(96.493)	(52.560)	(84.585)	(94.877)	(71.297)
Controls	N	N	N	Y	Y
Quarter FE	N	Y	Y	N	Y
Physician FE	N	N	Y	N	Y
N	2,289,126	2,289,126	2,289,126	2,258,742	2,258,736

Table A.3: Telemedicine Licensure Compact Treatment Effect and Physician Located on State Borders

This table shows the heterogeneous Telemedicine Licensure Compact treatment effects due to physician locations. $Border_i$ is one if physician i locates on state borders, and zero otherwise. There exists no physicians whose $Border_i$ changed in our sample period, so the coefficient of $Border_i$ is not identified given the *Physician FE*. $Compact_{i,t}$, and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, and Medicare utilization information is at an annual frequency. So the year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and year fixed effect *Year FE* is included for the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) ***LicenseNum***	(2) ***Log(MedService)***	(3) ***Log(MedBenes)***	(4) ***Log(MedPay)***	(5) ***Log(MedStdPay)***
$Compact_{i,t}$	0.016***	0.029***	0.018***	0.019***	0.013***
	(4.618)	(4.696)	(4.599)	(3.546)	(2.647)
$Border_i \times Compact_{i,t}$	−0.001	−0.028***	−0.009*	−0.016**	−0.007
	(−0.197)	(−3.459)	(−1.769)	(−2.273)	(−1.026)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.82	0.89	0.89	0.88	0.90

Table A.4: Telemedicine Licensure Compact and Hospital Utilization

This table shows that rural hospitals become less crowded following the shock. The panel unit is a yearly hospital observation. $Compact_{j,t}$ is one if hospital j's state has joined the Compact in time t, and zero otherwise. $Metro_j$ is one if hospital j locates in metropolitan areas, and zero otherwise. There exists no hospital whose $Metro_j$ changed in our sample period, so the coefficient of $Metro_j$ is not identified given the *Hospital FE*. $DischargeRate_{j,t}$ is the number of discharged patients per bed in hospital j at year t. $BedUtilization_{j,t}$ is the average percent of time that hospital j's beds are occupied in year t. The coefficients of control variables are omitted for saving space. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)
	DischargeRate	***BedUtilization***
$Compact_{j,t}$	−0.395*	−0.006***
	(−1.826)	(−2.901)
$Metro_j \times Compact_{j,t}$	0.821**	0.013***
	(2.366)	(4.246)
Controls	Y	Y
Year FE	Y	Y
Hospital FE	Y	Y
N	26,948	26,945
$adj.R^2$	0.89	0.96

Table A.5: Within-State Telemedicine Licensure Compact Effects

This table shows the Telemedicine Licensure Compact treatment effect with more granular fixed effects. In column (1), we replace the year-quarter fixed effect *Yr-Qtr FE* with the state-year-quarter fixed effect *State-Yr-Qtr FE*. In the remaining columns, we replace the year fixed effect *Year FE* with the state-year-quarter fixed effect *State-Year FE*. Since $Compact_{i,t}$ varies at state-time level, its coefficient is not identified with these granular fixed effects. Other variables are defined in the same way as Table 2. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Metro_i \times Compact_{i,t}$	0.025***	0.074***	0.053***	0.077***	0.069***
	(3.093)	(4.845)	(5.311)	(5.650)	(5.275)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
State-Yr-Qtr FE	Y	N	N	N	N
State-Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.79	0.88	0.88	0.87	0.89

Table A.6: Telemedicine Licensure Compact Effects and Local Healthcare Markets

This table shows the Telemedicine Licensure Compact treatment effect when controlling for local healthcare market conditions. In column (1), we replace the year-quarter fixed effect *Yr-Qtr FE* with the HRR-year-quarter fixed effect *HRR-Yr-Qtr FE*. In the remaining columns, we replace the year fixed effect *Year FE* with the HRR-year-quarter fixed effect *HRR-Year FE*. Other variables are defined in the same way as Table 2. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	LicenseNum	***Log(MedService)***	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	−0.019*	−0.030	−0.033**	−0.050***	−0.038**
	(−1.677)	(−1.491)	(−2.473)	(−2.736)	(−2.223)
$Metro_i \times Compact_{i,t}$	0.031***	0.052***	0.045***	0.059***	0.047***
	(3.778)	(3.215)	(4.354)	(4.132)	(3.511)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
HRR-Yr-Qtr FE	Y	N	N	N	N
HRR-Year FE	N	Y	Y	Y	Y
N	1,797,673	508,122	508,122	508,122	412,311
adj. R^2	0.81	0.89	0.89	0.88	0.90

Table A.7: Telemedicine Licensure Compact Treatment Effect and Broadband Coverage

This table shows the heterogeneous Telemedicine Licensure Compact treatment effects due to local internet broadband coverage. $PoorInt_i$ is one if physician i's county has the average percentage of rural population without broadband services greater than the sample 90^{th} percentile (62%), and zero otherwise. $Compact_{i,t}$, $Metro_i$ and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, and Medicare utilization information is at an annual frequency. So the year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and year fixed effect *Year FE* is included for the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	Log(MedService)	***Log(MedBenes)***	***Log(MedPay)***	***Log(MedStdPay)***
$Compact_{i,t}$	−0.069***	−0.043***	−0.071***	−0.065***
	(−4.782)	(−4.589)	(−5.435)	(−5.207)
$PoorInt_i \times Compact_{i,t}$	0.095***	0.073***	0.082***	0.078***
	(6.521)	(8.275)	(6.813)	(6.756)
$Metro_i \times Compact_{i,t}$	0.084***	0.054***	0.081***	0.074***
	(5.621)	(5.617)	(6.094)	(5.793)
Controls	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	617,388	617,388	617,388	521,644
adj. R^2	0.87	0.88	0.87	0.89

Table A.8: Telemedicine Licensure Compact Treatment Effect on Drug Promotion Payment

This table shows the Telemedicine Licensure Compact treatment effects on drug company promotion payments. $Log(AdvPay)_{i,t}$ is the logarithm of (one plus) physician i's total promotion payments from drug companies in quarter t. $Compact_{i,t}$, $Metro_i$, $Telescore_{i,t-1}$ and the outcome variables are defined in the same way as Table 2. The coefficients of control variables are omitted for saving space. *Physician FE* is the physician fixed effect. *Yr-Qtr FE* is the year-quarter fixed effect. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) ***Log(AdvPay)***	(2) ***Log(AdvPay)***	(3) ***Log(AdvPay)***
$Compact_{i,t}$	0.016*** (2.691)	−0.037* (−1.673)	−0.123*** (−8.314)
$Telescore_{i,t-1} \times Compact_{i,t}$		0.011** (2.442)	
$Telescore_{i,t-1}$		−0.002 (−1.262)	
$Metro_i \times Compact_{i,t}$			0.156*** (9.875)
Controls	Y	Y	Y
Physician FE	Y	Y	Y
Yr-Qtr FE	Y	Y	Y
N	2,258,736	1,493,061	2,258,736
adj. R^2	0.61	0.63	0.61

Table A.9: Evaluation of Treatment Effects by Cohorts Based on Participation Years

This table shows the Telemedicine Licensure Compact treatment effect across different cohorts based on the year when the state joined the Compact. $Compact_{j,t}^{2015}$ is one if the state joined the compact in 2015 and t is greater than both the actual Compact operation year (2017) and the state participation year (in this case 2015), and zero otherwise. $Compact_{i,t}^{2016}$ and $Compact_{i,t}^{2017}$ are defined similarly, except that $Compact_{i,t}^{2017}$ include both the 2017 and 2018 cohort since the 2018 cohort is small. Other variables are defined in the same way as Table 2. The coefficients of control variables are omitted to save space. *Physician FE* is the physician fixed effect. The licensure information is available at a quarterly frequency, Medicare utilization information at an annual frequency. Thus, a year-quarter fixed effect *Yr-Qtr FE* is included in column (1), and a year fixed effect *Year FE* is included for the remaining columns. Standard errors are clustered at the physician level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) ***LicenseNum***	(2) ***Log(MedService)***	(3) ***Log(MedBenes)***	(4) ***Log(MedPay)***	(5) ***Log(MedStdPay)***
$Compact_{i,t}^{2015}$	−0.013	−0.075***	−0.056***	−0.078***	−0.065***
	(−1.224)	(−3.632)	(−4.162)	(−4.252)	(−3.735)
$Compact_{i,t}^{2016}$	−0.016	−0.036*	−0.005	−0.033*	−0.035*
	(−1.597)	(−1.650)	(−0.366)	(−1.653)	(−1.836)
$Compact_{i,t}^{2017}$	−0.008	−0.027	−0.030	−0.065	−0.061
	(−0.324)	(−0.569)	(−0.950)	(−1.631)	(−1.637)
$Metro_j \times Compact_{i,t}^{2015}$	0.026**	0.061***	0.034**	0.054***	0.048***
	(2.246)	(2.877)	(2.431)	(2.857)	(2.677)
$Metro_j \times Compact_{i,t}^{2016}$	0.033***	0.096***	0.063***	0.093***	0.087***
	(3.143)	(4.215)	(4.331)	(4.544)	(4.388)
$Metro_j \times Compact_{i,t}^{2017}$	0.012	0.091*	0.091***	0.125***	0.102***
	(0.468)	(1.840)	(2.722)	(3.000)	(2.599)
Controls	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Yr-Qtr FE	Y	N	N	N	N
Year FE	N	Y	Y	Y	Y
N	2,258,736	617,388	617,388	617,388	521,644
adj. R^2	0.79	0.87	0.88	0.87	0.89

Table A.10: Treatment Effects from All Licensure Compacts

This table evaluates the effects of having any type of licensure compacts. The panel unit is a yearly hospital observation. $AllCompact_{j,t}$ is one if hospital j's state has joined any type of licensure compacts in time t, and zero otherwise. $Metro_j$ is one if hospital j locates in metropolitan areas, and zero otherwise. There exists no hospital whose $Metro_j$ changed in our sample period, so the coefficient of $Metro_j$ is not identified given the *Hospital FE*. $Log(Rev)_{j,t}$ is the logarithm of (one plus) hospital j's total revenues in year t. $Log(NetRev)_{j,t}$ is the logarithm of (one plus) hospital j's net revenues after insurers adjust for contractual allowances in year t. $Log(Patient)_{j,t}$ is the logarithm of (one plus) hospital j's discharged patients in year t. $Log(Salary)_{j,t}$ is the logarithm of (one plus) hospital j's average employee salary in year t. The coefficients of control variables are omitted for saving space. Year and hospital fixed effects are included, as indicated. Standard errors are clustered at the hospital level and t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1) ***Log(Rev)***	(2) ***Log(NetRev)***	(3) ***Log(Patient)***	(4) ***Log(Salary)***
$AllCompact_{j,t}$	−0.039**	−0.035**	−0.059***	−0.019***
	(−2.046)	(−1.983)	(−7.196)	(−5.177)
$Metro_j \times AllCompact_{j,t}$	0.054***	0.018	0.098***	0.031***
	(3.217)	(1.236)	(11.219)	(8.090)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
N	26,969	26,956	26,950	27,302
adj. R^2	0.98	0.97	0.99	0.91

Figure A.1: Early Adopter Compact Treatment Effect: Coefficient Dynamics

This figure plots the coefficient dynamics of Telemedicine Licensure Compact treatment effects of the early adopting states. An early adopting state is one that joined the Compact by 2016Q4. To generate this picture, we only keep early adopting states in the treatment group. Each coefficient is defined as $Early_t^s$, which is one if the physician is in an early adopting state and t equals to calendar time s, and zero otherwise. We replace $Compact_t^s$ in Equation (2) with $Early_t^s$, and plot the coefficients below. For example, in Figure (a), when $s = 2015Q2$, the coefficient estimates the difference between the early adopting states and control states in 2015Q2, relative to the references periods before the earlier adoption. 95% confidence intervals are indicated by the solid lines. Figure titles indicate the outcome variables corresponding to Table 2.