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Healthcare Across Boundaries: Urban-Rural Differences in the 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. We consider a quasinatural experiment: states' entry into the Interstate Medical Licensure Compact, wherein the entry events facilitate healthcare providers to adopt telehealth technology. By analyzing a representative sample of providers, we first establish the Compact entry shock's validity and its positive effect on the supply of medical services. We then report evidence that there are service and payment shifts from rural providers to urban providers (i.e., urban providers are more likely to benefit from the Compact entry financially). Relying on patients' telehealth reimbursement claim data, we observe two mechanisms contributing to the revenue redistribution: the substitution and gateway effects of telehealth. Finally, we show that telehealth readiness and service quality moderate the impact of telehealth adoption. These findings speak to both potentially positive and negative consequences for welfare.

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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 costs and improve the quality of care (Hersh et al. 2001, Jennett et al. 2003). However, with rare exceptions (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 most important considerations in providers' decisions of whether and when 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 (ITs), particularly the internet, 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 may be threatened. With these prospects on the horizon, healthcare administrators lack guidance on where, when, and how telehealth services are likely to shift competition patterns 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. More formally, we address the following questions in this work. How does telehealth technology adoption affect competition and the relative financial performance of healthcare providers across geographic regions? What are the underlying channels that redistribute patient flows through telehealth services? What are urban providers' competitive edges in serving patients virtually?

Answering these questions requires that we overcome several empirical challenges. 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.

We exploit states' staggered entry into the Interstate Medical Licensure Compact (the Compact hereafter), beginning in 2015, as a quasinatural experiment, wherein entry events incentivize providers to adopt telehealth technology and engage in telehealth service delivery.[1] 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 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 broader geographic scope of patients, yielding greater financial benefits from telehealth technology adoption.[2]

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 telehealth expenditures through a representative, proprietary, claim-level database that covers approximately 14% of all insured individuals in the United States.

We first demonstrate that the Compact entry associates with a clear increase in the supply of medical services (potentially through telehealth adoption). As expected, we document a significant rise in physicians' applications for additional state licenses following host state's Compact entry. We also document increases in the payments affected physicians 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.[3] We subsequently hypothesize that patterns of adoption and associated financial benefits differ markedly between urban and rural providers before presenting a variety of supporting evidence.

We begin descriptively, noting that our claims data demonstrate rural patients' clear preference for urban providers when it comes to telehealth services; indeed, more than 80% of rural patients' telehealth claims involve urban providers. Further, we show that urban providers in a state begin to acquire more state licenses systematically after their state joins the Compact. Next, we show that these shifts are accompanied by greater revenue among urban providers. Financially, affected urban providers experience a systematic increase in Medicare service activity, patient volumes, and payments. We estimate that affected urban physicians' claimed Medicare service amounts increase by 2.4% and that payments increase by 1.9%. In aggregate, affected urban hospital revenues rise by 2.6%. In contrast, we estimate that affected rural providers experience declines in all these outcomes; rural physicians' claimed Medicare payments decrease by 5.6%, and rural hospitals experience a 4.6% decline in revenue. We establish the robustness of these findings to various empirical concerns (e.g., potential bias in the two-way fixed effect (TWFE) estimator under the staggered entry and confounding policy shocks).

We next evaluate the mechanisms that contribute to the observed revenue redistribution between urban and rural providers, focusing on two in particular. The first mechanism we examine is substitution (Ayabakan et al. 2020), wherein rural inpatients may transition to urban (telehealth-mediated) outpatients. The second, indirect mechanism that we consider is a possible gateway effect (Bavafa et al. 2018), wherein rural patients follow up their virtual (outpatient) visits with in-person (inpatient) visits to urban providers. We provide evidence in support of both channels, leveraging our claims data. First, we show that affected rural patients (i) increase their expenditures toward urban-provided telehealth services by 7.6% and (ii) increase their expenditures toward urban-provided follow-up visits by 8.6%. At the same time, we show that rural patients significantly reduce their in-person and telehealth expenditures toward local (rural) providers.

Finally, we examine contextual factors that may moderate or contribute to these outcomes. In particular, we provide results that speak to two relative advantages held by urban physicians: better telehealth readiness and higher service quality. We show that affected urban providers experience 6.6% higher service flows and receive 3.8% more revenue if their affiliated hospital has fully implemented telehealth services at the time of Compact entry. Similarly, urban physicians experience 3.4% higher service flows and receive 3.0% more payment upon Compact entry if their affiliated hospital ranks in the top quartile of overall quality versus the bottom quartile.

Collectively, these findings support the conclusion that telehealth service expansion results in a revenue shift from rural to urban providers and hospitals, consistent with recent anecdotal evidence.[4] Our findings also speak to the potential for both positive and negative welfare consequences from states' Compact entry. In the absence of telehealth options, rural patients may be forced to obtain their healthcare services from local, rural healthcare providers because of the larger travel costs associated with visiting urban providers. With the help of telehealth, underserved rural patients gain access to a wider pool of potential providers. This dynamic raises the concern that telehealth services may exacerbate the already tenuous financial situation among rural hospitals in the United States.[5] Over the long term, the availability and quality of emergency medical services in rural areas may be under threat.

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 primarily theoretical in nature (Rajan et al. 2013, 2019). For example, Rajan et al. (2013) considers two asymmetric hospitals—one with telemedicine and the other without telemedicine—and predicts that the telehealth adopter will steal market share from its competition. Our urban-rural framework mirrors this setup; we document that urban providers have comparative advantages in their telehealth readiness and service quality, whereas rural providers are analogous to the nonadopter in their setup. Our results have important implications for policy makers and raise 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 patients' satisfaction and quality of care? At present, most rural hospitals only serve as the originating site, and they are not responsible for follow-up treatments; hence, they only receive an approximately $25 facility fee. In Section 5, we thus suggest that allowing rural and urban hospitals to provide complementary services can create mutual benefits for both providers. This suggestion echoes the extension of Rajan et al. (2013) by allowing some local community hospitals to service in-person follow-up visits after telehealth services are delivered by distant telehealth providers.

We also contribute to the literature by highlighting a relatively understudied, nationwide quasiexperimental research design, namely Compact entry as a shock to local telehealth adoption. A majority of previous work has limited its consideration to a single provider, hospital system, or state. We exploit this regional regulatory decision to examine effects on providers' operating in numerous states across varied geographies and markets. This approach enables the application of an intuitive econometric specification (difference in differences (DID)) and allows us to combine different sources of healthcare data across various states to generate a comprehensive evaluation. This offers the benefit of generalizability, despite the inherent challenge of self-selection that needs to be borne in mind.

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" (physician-patient digital messaging) 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 address demand surges and supply shortages better. 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 nonchronic patients, as they estimate that inpatient admissions increase by approximately 45%. More broadly, Salge et al. (2022) show that information technology helps hospitals gain and sustain a reputation in the media, and Wang et al. (2020) demonstrate that physicians' online activities can bring a higher service quantity in offline channels.

Our focus in this paper is unique in at least two respects. (i) We evaluate telehealth adoption's competition effect, and (ii) our results do not derive from data describing a single-provider system or state. On the contrary, Compact entry is an *interstate* policy shock that reshapes the competitive landscape beyond state borders. Reflecting this, a recent 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 the competition begins to manifest across regions (e.g., between states). Although some work has examined patterns of crossmarket competition (Dafny et al. 2019), that work was focused on the notion of mergers between geographically distant hospitals.

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 that 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 theoretical relationships.

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 on Amazon and show that online sales diminish when a brick-and-mortar bookseller opens nearby. More recently, Overby and Forman (2015) examine the introduction of digital sales channels in the market for used vehicles. Those authors report evidence that the introduction of digital channels increases price transparency and reduced price dispersion, as buyers use the channels 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 that they typically face higher transportation costs to access inpatient healthcare services.

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 U.S. Medical Licensing Examination, state medical boards often have other idiosyncratic licensure requirements that they impose on physicians, including citizenship requirements, educational requirements, Federal Bureau of Investigation (FBI) criminal background checks, 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.[6] A typical application takes 4–12 weeks, and in some states, such as California, it takes as long as seven months.[7] Time and effort aside, physicians also have to pay an approximately $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.[8] 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, near 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 have already met. In a single application, a physician residing within the Compact may 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 procedures to streamline the license acquisition process. On average, it takes just 19 days to acquire all Compact state licenses.

Member states gradually announced their intention to participate in the Compact beginning in 2015. By April 2017, there was a sufficient number of participating

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states, and the Compact started to operate. The timing of member states' entry into the Compact is depicted visually in Figure 1. In Section A.1 in the online appendix, we provide a complete list of state bills codifying states' Compact participation and the dates when each bill went into effect. In addition, to understand the nature of the Compact entry decision, we collected anecdotal reports of states' rationale for participation from various news sources and press releases. An oft-cited reason for Compact entry is that states hope to address gaps in service delivery for rural patients by expanding patient access to telehealth providers. For example, when introducing the Compact during a public hearing, Senator Kolterman of Nebraska stated: "Telemedicine and technology are changing healthcare, but our licensure process is falling behind. For many Nebraskans, especially in rural areas, this committee knows, better than anybody, that access to in-person clinical services because of transportation limitations and lack of available physicians is often a challenge which results in poor health outcomes."[10] Other legal reasons for Compact entry are also discussed in Section A.1 in the online appendix.

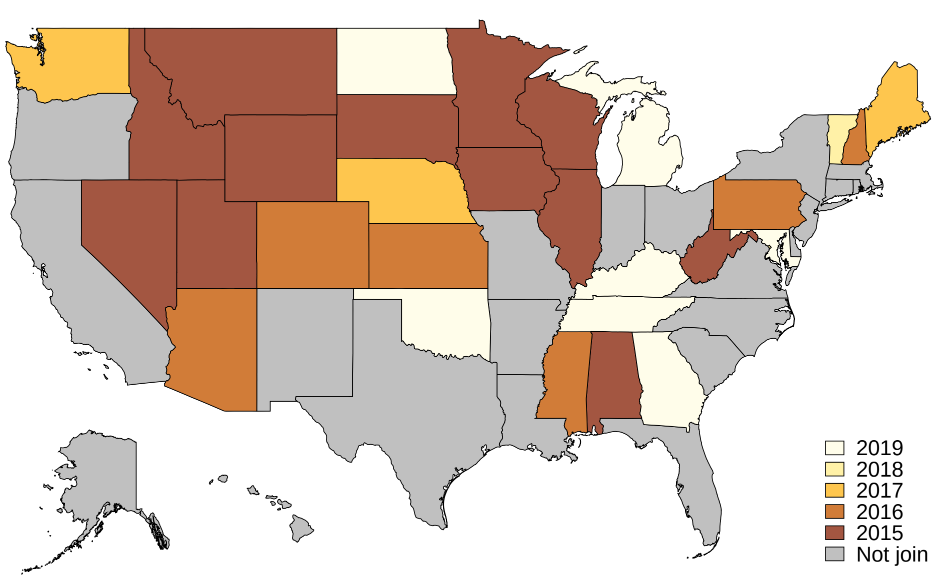
We leverage states' staggered entry into the Compact as a shock to the prevalence of telehealth providers in a state. Because the Compact officially went into effect on April 6th, 2017, we use that quarter (i.e., 2017Q2) to operationalize entry timing for those states that approved Compact participation prior to that time.

A possible concern with this empirical strategy is that states' Compact entry reflects a process of self-selection (i.e., states bearing certain unobserved characteristics may be more likely to opt into the Compact), and some of those characteristics may also drive systematic differences in our outcomes of interest. Were this the case, any differences we observe between urban and rural providers' outcomes might result from such unobservable factors rather than the event of interest, namely Compact entry and the ensuing expansion of telehealth services. We evaluate the self-selection concerns in relation to the following aspects in Online Appendix Section A.1.

First, in Table A.2 in the online appendix, we explore potential systematic differences between the 30 treated states (including Washington, DC) and the other 21 control states along several important dimensions. We estimate a Cox proportional hazard model of Compact entry to determine the factors predicting Compact entry. The dimensions we consider include measures of telehealth usage, healthcare inequality between urban and rural geographies, population demographics, geographic positioning within the United States, and telehealth readiness. Importantly, we do not find evidence that Compact entry is significantly associated with any of these factors. Table A.3 in the online appendix confirms that our results satisfy the proportional hazards assumption for each independent covariate and all of them jointly.

Second, we report a comparison of sample variable means between treated and control states in Table A.4 in the online appendix. Across all comparisons, the only marginally statistically significant difference arises around state population ($p < 0.10$), which may raise the concern that Compact entry is a function of the size of a state's healthcare market. However, it should be noted that some large states have joined the Compact quite recently (e.g., Texas joined in June 2021) and that others

Figure 1. (Color online) States' Compact Entry Year



Notes. This figure plots the year when a state joined Compact. DC joined in 2018. Grey areas are the non-Compact states in our sample. Since the Compact became operational on April 6th, 2017, we use 2017Q2 as the first treatment period for the states joining earlier than this date.

have introduced legislation to do so (e.g., New York in March 2021). Nonetheless, to address any concerns about selection, we replicate our main results by omitting the most highly populated nonmember states from our estimation sample. In Tables A.5–A.9 in the online appendix, we show that our results are robust to omitting California, New York, Texas, or Florida either jointly or individually.

Further, we address two other potential endogeneity concerns around the Compact entry. First, in theory, states with large inequalities in urban-rural healthcare may have greater incentive to join the Compact. If this is the case, rural patients in such states might try to seek urban providers, regardless of the Compact entry, and this might drive, or at least partly explain, the observed urban-rural shift. We construct two measures of healthcare inequality based on the rural-to-urban ratio of patient volumes and hospital employees in each state as of 2014, the year prior to the initial Compact formation. We then split states into two groups based on the median value of each ratio, and we focus on states that are *not* characterized by a high degree of urban-rural inequality. We replicate our focal analysis and find that our results continue to hold in Tables A.10 and A.11 in the online appendix, with effect magnitudes that are quite similar to those reported in our main results. Second, states with large hospital systems may have an incentive to lobby for Compact entry. Large hospital systems often operate across state borders, and they would thus stand to benefit disproportionately from greater physician geographic mobility and flexibility within the Compact. Importantly, because these sorts of large hospital systems have a great deal of market power, they may also have the capacity to attract patients from rural areas, perhaps even without Compact entry. Considering this, we construct another state-level measure, reflecting the 2014 fraction of hospitals in the state that were affiliated with a hospital system, and we again split states into two groups at the median. Focusing on states that are *not* dominated by hospital systems, our results continue to hold (see Table A.12 in the online appendix).

Lastly, cognizant that our Cox proportional hazard models assessing self-selection in states' Compact entry may fail to capture important, time-varying features of a state or its local healthcare market, we replicate our key results (e.g., those related to urban-rural differences) while separately incorporating state-time and hospital referral region-time fixed effects. These robustness checks appear in Tables A.13 and A.14 in the online appendix. State-time fixed effects will absorb unobserved factors varying over time across a state that may also affect the Compact entry decision. Similarly, hospital referral region-time fixed effects will account for such unobserved factors that vary over time across a regional healthcare market for tertiary medical care (e.g., changes in local market structure). Again, we observe robust urban-rural differences under these estimations.

3.2. Data

We collect data from several sources at the physician, patient, and hospital levels. Tables 1–3 provide detailed summary statistics for all variables. We next describe the steps that were taken to construct our estimation samples.

3.2.1. Physician Sample. We first collect granular data on physician licensure from the Open Payment database. Drug companies frequently make promotion payments to physicians in the United States in exchange for prescribing their drugs to patients. Under the Patient Protection and Affordable Care Act, drug companies are required to report any such physician payment or in-kind "transfer of value" in the Open Payment database.[11] We obtain data from August 2013 (when the database begins) through the end of 2018. Each observation in the database pertains to a firm-physician encounter (i.e., a transaction between a firm and a provider), documenting the company and the physician's information, the focal drug, the dollar amount of the payment, and the payment date. Of particular relevance to our study, the drug company reports up to five state licenses held by the physician at the time of the payment. We aggregate this information to physician-quarters, taking the total number of unique, active state licenses held by the physician over the two years prior.[12] We then merge the physician-quarter panel 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 be nonmissing, ensuring that we have location information and control variables associated with the physician's workplace. Lastly, we match the physicians to the CMS Medicare Fee-for-Service Provider Utilization & Payment Data Public Use File (Provider PUF) based on the NPI. This database records services and procedures provided to Medicare beneficiaries by physicians and other healthcare professionals under Medicare (fee-for-service) Part B (Medical Insurance). Note that, whereas the licensure information is constructed on a quarterly basis, the utilization summary is aggregated only on an annual basis. The final physician sample consists of 2,289,126 quarterly observations and 631,047 annual observations associated with 139,696 unique doctors. The physicians in our sample represent approximately 19.4% of all registered physicians affiliated with Medicare hospitals in 2020.[14] Online Appendix Section A.2 discusses the sample construction process in more detail.

Two other aspects of our sample construction are worth noting. First, because some physicians do not receive payments every quarter, we delete those physicians where more than half of all observations are

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Table 1. Summary Statistics: Physician Sample

Variable	Variable definition	*N*	Mean	Standard deviation	Median
$Compact_{i,t}$	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
$MidSeniority_{i,t}$	Whether physician *i* has graduated for 10–25 years in year *t*	631,047	0.488	0.500	0.000
$PastAction_{i,t}$	Whether physician *i* has received warning by year *t*	631,047	0.009	0.094	0.000
$HosRating_{i,t}$	% of patients giving the highest overall ratings in physician *i*'s working hospital in year *t*	618,468	0.711	0.072	0.720
$HosDischarge_{i,t}$	No. of patients discharged (in 10,000 s) from physician *i*'s working hospital in year *t*	628,386	1.956	1.679	1.579
$HosIncome_{i,t}$	Annual income (in millions) of physician *i*'s working hospital in year *t*	628,484	589.234	684.423	376.977
$HITRatio_{i,t}$	% HIT assets over total assets of physician *i*'s working hospital in year *t*	627,680	0.004	0.020	0.000
$FullTele_{i,t}$	One if physician *i*'s working hospital has fully implemented telehealth in all units in year *t*	631,047	0.068	0.251	0.000

missing between 2013Q3 to 2018Q4. We take this step to alleviate the concern that our licensure information is subject to reporting lags. Second, when merging the Open Payment database with the Provider PUF database, we generate a physician sample containing both licensure and Medicare payment information. To alleviate the concern that either step may introduce a selection bias, we demonstrate that our main results (those related to urban-rural differences) are robust in a broader sample. We also provide a detailed list of physician primary

Table 2. Summary Statistics: Hospital Information

Variable	Variable definition	*N*	Mean	Standard deviation	Median
$Metro_{j}$	Whether hospital *j* is in a metropolitan area	27,399	0.542	0.498	1.000
$Compact_{j,t}$	Whether the state of hospital *j* joins Compact by 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
$ServiceHour_{j,t}$	Hospital *j*'s total net service hours (in thousands)	19,963	2,660.731	3,628.831	1,552.489
$Patient_{j,t}$	Hospital *j*'s number of discharged patients in year *t*	27,050	6,856.902	9,601.197	2,892.918
$Income_{j,t}$	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

Table 3. Summary Statistics: Patient Sample

Variable	Variable definition	N	Mean	Standard deviation	Median
$Compact_{k,t}$	Whether the state of patient k joins Compact by year t	435,832	0.199	0.400	0.000
$TelePay_{k,t}^{Urban}$	Telehealth payments to urban providers by patient k in year t	435,832	78.026	237.479	40.000
$TelePay_{k,t}^{Rural}$	Telehealth payments to rural providers by patient k in year t	435,832	2.505	81.824	0.000
$GatePay_{k,t}^{Urban}$	In person follow-up payments to urban providers by patient k in year t	191,861	1,051.160	11,525.300	84.000
$GatePay_{k,t}^{Rural}$	In person follow-up payments to rural providers by patient k in year t	191,861	60.872	1,480.732	0.000
$Age_{k,t}$	Age of the patient	435,832	35.693	15.596	36.000
$Enroll_{k,t}$	Length of enrollment since 2012	435,832	1.792	0.374	1.946
$Working_{k,t}$	Whether patient is working	435,832	0.942	0.235	1.000
$Standard_{k,t}$	Whether patient has standard medical insurances	435,832	0.004	0.063	0.000

specialties, and we confirm that nonmedical providers, such as nurse practitioners and physician assistants, are uncommon in our sample.

Table 1 summarizes the physician sample. We find that roughly 14% of our sample observations are "treated" by state Compact membership. Note that this percentage does not include pre-shock periods for the eventually treated doctors. The size of this treatment group is nontrivial; 41,180 physicians, or 29.5% of the physician sample, work in a state that eventually joined the Compact. On average, physicians only apply for 1.38 licenses, and more than half of the physicians solely service patients residing 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 that, after 2014, CMS applies a standardization process to account for local economic and healthcare conditions when generating the variable $MedStdPay_{i,t}$. The average of this variable is thus slightly higher (\$196,670) than that of the unadjusted value. Lastly, physicians in our sample receive \$972.52 in quarterly average promotional payments from drug companies. The other measures are control variables, which are explained in the next section.

3.2.2. Hospital Information. To study the urban-rural differences, we need to identify the physician's working location. We first match the physicians to county Federal Information Processing System codes based on their affiliated hospital's zip code, and then, we categorize counties as urban or rural based on rural-urban commuting area (RUCA) codes. Rural counties are defined as those in nonmetropolitan areas, having an RUCA code strictly greater than three. As Table 2 shows, more than 54% of the hospitals in our sample are located in urban areas.

In our analyses involving the physician sample, we control for the financial and quality characteristics of affiliated hospitals. Most hospitals are required to provide an annual cost report to CMS in the Healthcare Cost Report Information System (HCRIS), covering operational details of hospitals. For control variables, we collect the number of discharged inpatients, the amount of hospital income, and health information technology (HIT) designated assets. To measure hospital quality, we merge HCRIS data with data from the Hospital Consumer Assessment of Healthcare Providers and Systems, which is a patient satisfaction survey required by CMS that is 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. In our hospital-level analysis in Table A.32 in the online appendix, we focus on four main outcome variables: total revenues, net revenues, total service hours, and number of patients discharged. The other variables in Table 2 are control variables for the hospital-level analysis.

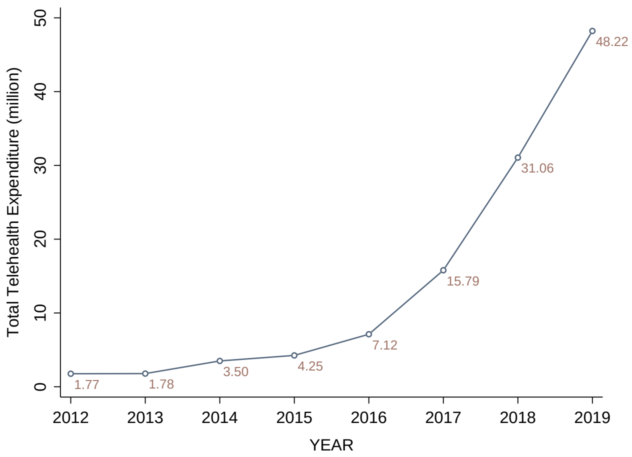
3.2.3. Patient Sample. To provide concrete evidence of telehealth's role, we utilize the IBM Marketscan database, which contains deidentified patient healthcare reimbursement information. IBM reports that this data set captures healthcare claims activity associated with employees, retirees, and dependents insured via 260 medium and large employers across 40 health plans. The broader database covers over 43 million privately insured individuals who presently or previously drew upon employment-based health plans. We focus, in particular, on the inpatient and outpatient service files, capturing healthcare services from 2012 through 2019. To provide context, approximately 33 million individuals appeared at least once across these two files between 2017 and 2019. As the total insured population in the United States is roughly 296 million people, the IBM Marketscan database captures healthcare activity associated with roughly 14% of the total insured population, and our inpatient and outpatient service files cover approximately 11% of the insured population.

Each observation in the Marketscan database represents a claim, documenting patient identification (ID) and provider ID (both are persistent and deidentified), diagnosis codes, procedure codes, payments, revenue codes, place of service, patient location, and service date. Because the reimbursement requirement of telehealth services has changed repeatedly during our study period, we focus on the claims satisfying at least one of the following criteria: (1) revenue code is 0780 (telemedicine—general classification) or 0789 (telemedicine—telemedicine); (2) procedure modifier is G0 (telehealth services furnished for purposes of diagnosis, evaluation, or treatment of symptoms of an acute stroke), GT (service via interactive audio and video telecommunications systems), 95 (an alternative to GT after 2017), or GQ (asynchronous services); (3) procedure group is 113 (physician telephone/online visits); or (4) place of service is 2 (telehealth).

In Figure 2, we aggregate the yearly total telehealth reimbursements. Marketscan claims data indicate there were \$31.06 million in telehealth reimbursement in 2018 alone and 48.22 million in 2019. Additionally, telehealth reimbursements doubled year over year from 2015 onward. Given that our inpatient and outpatient files cover approximately 11%–14% of the total insured population, we estimate that the total yearly reimbursements associated with telehealth likely are somewhere between \$222 million and \$282 million in 2018 and between \$344 million and \$438 million in 2019.

As noted earlier, one of the key mechanisms by which the telehealth adoption can influence providers' revenue is the telehealth gateway effect. In Table 3, we also define $GatePay^{Urban}$ and $GatePay^{Rural}$ to study the in-person follow up visits (i.e., nontelehealth visits that happen after the initial telehealth service date) for each patient-provider pair. For the full sample of urban and rural patients, 31.12% of the 433,462 patient-provider pairs have in-person follow-up visits within a year, and about 35% of them ever do so in the sample; this number increases slightly to 36.6% for rural patients, indicating that rural patients are at least as likely to follow up in person after the first telehealth visit. See Figure 3 for the cumulative probability over time.

Figure 2. (Color online) Total Telehealth Payments over Time



Notes. This figure plots the time series of total reimbursed telehealth payments (in millions of U.S. dollars) using the Marketscan data from 2012 to 2019. In recent years, this database covers over 43 million privately insured individuals with employment-based health plans, which represent roughly 14% of all of the insured U.S. population and 20% of all of the privately insured U.S. population. We generate the telehealth services from Marketscan inpatient and outpatient service files from 2012 to 2019. The number of active enrolled individuals, defined as those who had at least one claim in these two files from 2017 to 2019, is 33 million.

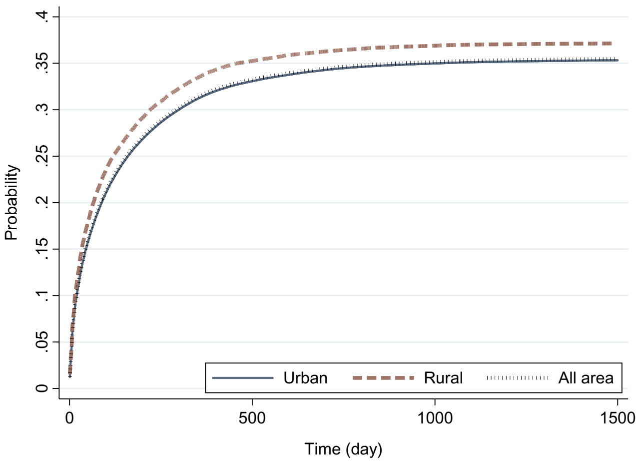
3.3. Conceptual Framework

We expect that the Compact will increase the number of physicians providing telehealth services in treated states and that this, in turn, will systematically benefit urban providers at the expense of rural providers. The rationale for this expectation is as follows.

First, absent the Compact, telehealth demand is restricted to the home state for most physicians because of licensing requirements. With entry to the Compact, providers can serve more out-of-state customers remotely, and their expected profits will increase. Accordingly, physicians should become more likely to initiate telehealth services. Along with increases in telehealth activity, we expect to observe that physicians acquire more state licenses, which are necessary for them to serve a broader market. Indeed, we will report evidence consistent with each of these expectations in Table 5.

Second, we argue that wider adoption of telehealth services will change the competitive landscape, leading to different outcomes for rural and urban providers. In

Figure 3. (Color online) Cumulative Probability of In-Person Visits After Telehealth Services



Notes. Using the Marketscan database, this figure plots the cumulative probability of continuing in-person treatments with the same provider after their telehealth services. The horizontal axis represents the number of days after the first telehealth service between a patient and a physician. The vertical axis represents the cumulative probability of following in-person treatments among all the telehealth patient-physician pairs. The three lines represent different patients when they are from rural, urban, or all areas.

Table 4. Geographic Distribution of Telehealth Providers

	Telehealth provider location		
	Urban	Rural	Sum
Patient location (rural), %	82.17	17.83	100.00

Notes. This table reports the geographic distribution of telehealth providers using the Marketscan data from 2012 to 2019. We calculate the percentage of telehealth service claims by rural patients that are provided by either urban or rural telehealth providers.

the United States, most telehealth policies aim to improve healthcare services in rural areas. Indeed, Compact language explicitly 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. This dynamic is reflected by the crosstabulation we report in Table 4, breaking down the joint distribution of urban versus rural locations of telehealth providers and patients based on our Marketscan claim data. Rural residents are much more likely to connect with urban physicians; rural patients connect with urban providers in 80% of their telehealth service interactions.[15] Therefore, urban providers will receive the majority of telehealth adoption benefits, leading to our hypothesis around urban-rural differences. We test this hypothesis in Table 5, and the findings are supported by a variety of detailed robustness checks in Section 4.2.

Third, we evaluate two telehealth-related mechanisms by which Compact entry may shift revenues from rural to urban providers. The first channel we consider is whether telehealth services offered by urban providers directly replace in-person services provided by rural providers (i.e., a substitution effect) (Ayabakan et al. 2020). The second related channel we consider is whether rural patients' consumption of telehealth services from urban providers makes rural patients more likely to consume in-person services from those urban providers (i.e., a gateway effect) (Bavafa et al. 2018, Ayabakan et al. 2020). We report empirical evidence supporting the role of both channels in Section 4.3.

Last, we study the comparative advantages of urban providers regarding telehealth services to understand why urban providers experience greater demand and preference from rural patients. In Section 4.4, we show that urban providers tend to have better telehealth technology readiness and higher service quality and that both factors amplify urban providers' financial benefits.

3.4. Empirical Specification

Our identification strategy exploits the staggered entry of states into the Compact. We leverage this quasinatural experiment to estimate a 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 a quarterly panel of physicians. In Equation (1), $Y_{i,t}$ reflects our outcome variables, including physician licenses, services, and payments. The variable $Compact_{i,t}$ is set to one if the physician's primary operating state participates in the Compact as of quarter t and zero otherwise. The variation of $Compact_{i,t}$

Table 5. Interstate Medical Licensure Compact Treatment Effect

	(1) *LicenseNum*	(2) log(*MedService*)	(3) log(*MedBenes*)	(4) log(*MedPay*)	(5) 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
Adjusted R^2	0.79	0.87	0.88	0.87	0.89

Notes. This table shows the Compact treatment effect using Equation (1). $Compact_{i,t}$ is one if, as of time t, the Compact had become operational and physician i's state has joined the Compact and zero otherwise. $LicenseNum_{i,t}$ is the number of active state licenses that physician i holds 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, and Medicare utilization information is 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. N, no; Y, yes.

***Statistical significance at the 1% level.

comes from whether and when a state joined the Compact. In terms of timing, 12 states had joined the Compact by the end of 2015, 6 joined in 2016, 3 joined in 2017, and 2 joined in 2018. Given that the Compact only became operational in 2017Q2, $Compact_{i,t}$ is set to one in that period for any states that joined prior. For our annual measures, we benefit from nearly two full years of posttreatment activity in most cases; for measures reported quarterly, we have six to seven posttreatment periods in most cases. The coefficient of interest, β, is our estimate of 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 TWFE model; later, we evaluate and rule out possible biases associated with this estimator (Goodman-Bacon 2021).

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 ($MidSeniority_{i,t}$). The logic here is that early-career physicians initially improve their quality of care through "learning by doing," but those learning effects stop later in their careers. 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 higher mortality than patients cared for by younger physicians. We also include an indicator for whether physician i has received disciplinary action from the medical board at any time up to and including quarter t ($PastAction_{i,t}$). We obtain these records from docinfo.org, and they reflect punitive actions against providers in response to unprofessional, incompetent, or improper medical practices, including drug abuse and off-label prescription.[16]

The second group of controls accounts for the characteristics of the physician's hospital, including the number of patients discharged in the previous year ($HosDischarge_{i,t-1}$), the fraction of patients giving the highest overall ratings on quality surveys in the previous year ($HosRating_{i,t-1}$), annual income (in millions) in the previous year ($HosIncome_{i,t-1}$), and the ratio of HIT assets over the hospital's total assets ($HITRatio_{i,t-1}$). If a physician works for multiple hospitals, we aggregate the volume of discharges and income across all employing hospitals while taking the average of the other two variables. For the sake of brevity, we report the coefficients associated with all control variables in Online Appendix Section A.3.

4. Results

4.1. Main Results

Table 5 reports the average treatment effect of Compact entry on several outcomes of interest. 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 because 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 estimate this relationship via Poisson regression in Table A.30 in the online appendix, where we find that the quarterly rate of new license applications increases significantly, by an estimated 9.4%, when a physician's host state enters the Compact.

Columns (2)–(4) document that Compact entry also drives increases in physicians' service amounts and revenues. We find that affected physicians provide significantly more Medicare services, treat more beneficiaries, and receive higher payments, with magnitudes ranging from 1.1% to 1.6%. 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. To put this number into context, the total reimbursement received by physicians in treated states was 8.21 billion US dollar in 2018; thus, a 1.1% increase because of Compact entry amounts to an additional 82.1 million US dollar. Column (5) demonstrates that the results remain consistent if we use the CMS standardized payment as our outcome variable, which adjusts for geographic differences in payment rates because of local wages, input prices, practice patterns, and beneficiary conditions.

Note that the treatment effect estimates reported in columns (2)–(4) pertain to all physicians located in treated states, regardless of whether they obtain more licenses. For the Compact to generate real impacts on a physician, it would be necessary for the physician to first obtain additional state licenses. Accordingly, in Table A.31 in the online appendix, we also estimate a local average treatment effect, interacting the *Compact* dummy with an *Apply* variable, which indicates whether a treated physician applied for additional licenses in the sample period. The coefficient associated with the interaction term in that regression is significant and positive, indicating that license-acquiring physicians experience significantly larger revenue effects. Moreover, the coefficient associated with *Compact* is significant and negative, suggesting that *only* complying physicians benefit financially from Compact entry.

The DID specification is only valid if the parallel trend assumption is satisfied. One way we can evaluate the assumption is by plotting dynamic coefficients across periods relative to the timing of treatment, as in Autor

(2003). Specifically, we estimate Equation (2):

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

In this equation, $Compact^s_{i,t}$ is set to one if, as of time t, the Compact had become operational and physician i's state had joined the Compact and zero otherwise. In the licensure sample, for example, $Compact^{-3}_{i,t}$ equals one for the quarter t that is three quarters before the state's Compact entry went into effect. The interpretation of β_s is thus the relative difference between the treatment and control groups s periods relative to 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 $s = -1$, allowing it to serve as the reference period (i.e., the benchmark difference). Figure 4(a) confirms that all coefficients in leading periods ($s \leq -2$) are statistically insignificant and are close to zero for *LicenseNum*, consistent with the assumption of parallel trends. Meanwhile, the treatment effects in the lagging periods are apparent. We obtain similar patterns of results if we plot the coefficients dynamics for effects related to our other remaining outcome variables in Table 5. However, because Medicare utilization data are aggregated yearly, it should be noted that there are only two treatment periods (years) in our sample following the shock.

Our main hypothesis is that substantial geographic heterogeneity exists around the treatment effects reported in Tables 1–3. In particular, we expect 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 effects will be much larger for urban providers and that financial effects would run in opposite directions for providers in urban versus rural areas. In Table 6, we evaluate this prediction by adding an interaction term, multiplying $Compact_{i,t}$ with $Metro_i$, which is set to one if physician i's working hospital is in a metropolitan area (based on whether the associated United States Department of Agriculture 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 strongly, exhibiting a 2.7% rise in licensure.

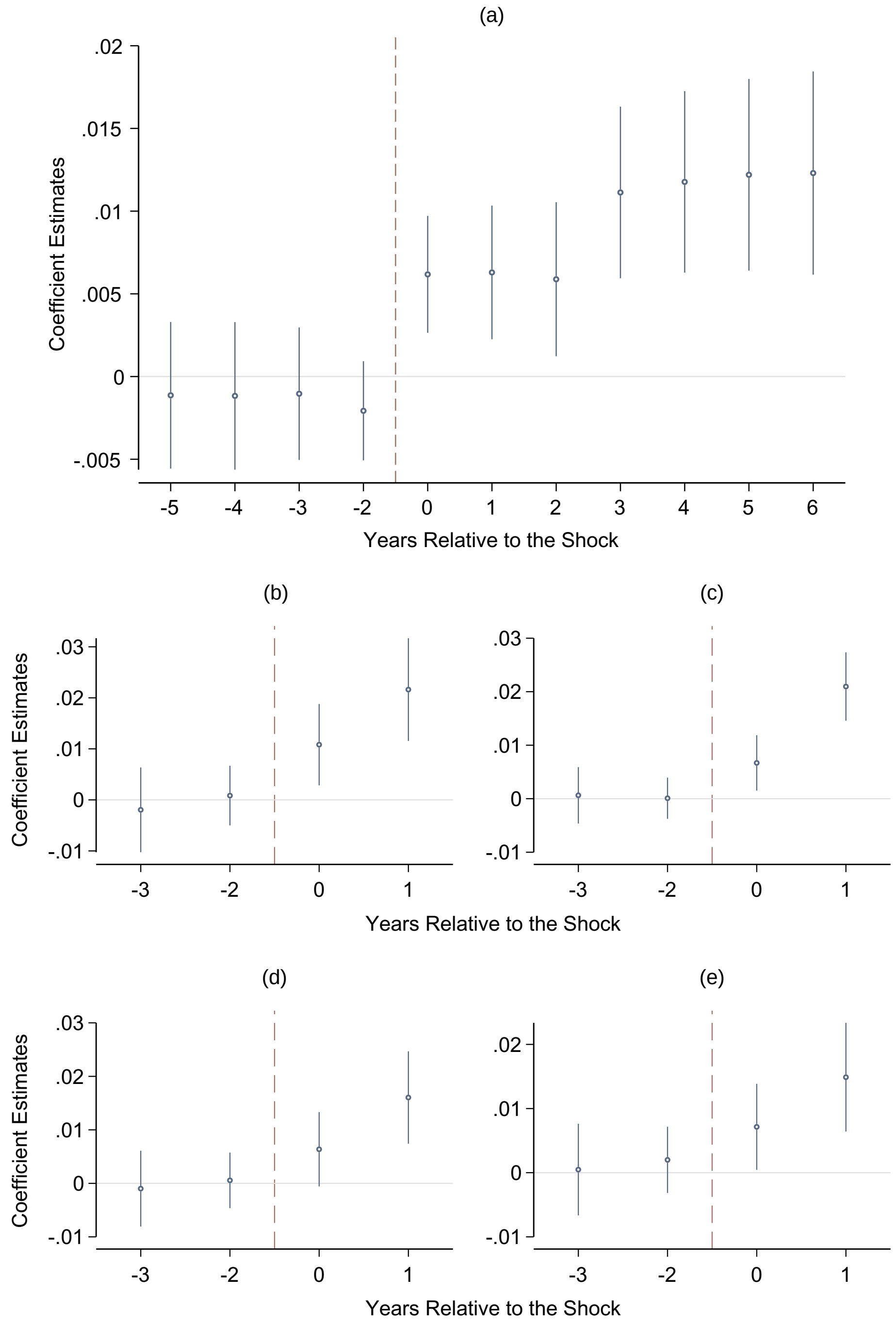
The remaining columns in Table 6 show that treated rural physicians suffer financially too, as their service amounts and payments from Medicare systematically drop by an estimated 3.1% and 5.6%, respectively, as indicated by the coefficients associated with $Compact_{i,t}$. Only urban providers truly benefit. For example, column (4) shows that their Medicare payments increase by 1.9% (−5.6% + 7.5%). In sum, although Table 5 demonstrates that the average treatment effects pooling urban and rural physicians together suggest broad benefits at first glance, breaking them apart yields stark differences, suggesting shifts from rural in-person services to urban telehealth services.

4.2. Robustness of Estimated Urban-Rural Differences

4.2.1. Hospital-Level Results. 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 physicians are engaged because they only reflect Medicare Part B reimbursements. Accordingly, to provide a complete picture of revenue effects, we also investigate hospital-level outcomes. These are reported in Table A.32 in the online appendix. If our hypothesized competition effect exists, then we would expect to obtain similar results in terms of revenues and patient flows at the hospital level. Our specification is similar to Equation (1), except that $Compact_{j,t}$ is defined for each hospital j in year t, and we include hospital-level dynamic controls, hospital fixed effects, and year fixed effects. The outcome variables in these analyses include total hospital revenues in column (1), net revenues in column (2), and total service hours in column (3). These variables capture *all* medical services delivered at a hospital, including both inpatient and outpatient services. Finally, in column (4), we consider inpatient discharges as a proxy for patient flows. The CMS HCRIS system does not require hospitals to disclose outpatient volumes, so we are unable to calculate outpatient measures in this sample. Column (1) shows that the affected rural hospitals experience a 4.5% decline in total revenue, whereas their urban counterparts experience a gain of 2.6% (−4.5% + 7.1%). The result is consistent if we use net revenues as our outcome variable, reflecting actual payments from insurers to providers, after contractual adjustments. Similarly, we find the total service hours of affected rural hospitals significantly decrease by an average of 3.2%, consistent with a loss of local healthcare service demand.

4.2.2. Robustness to Alternative Estimation Approaches. Goodman-Bacon (2021) shows the presence of potential biases in staggered DID settings and assesses whether and when a TWFE estimator will yield causally interpretable result. We implement some of alternative approaches in Online Appendix Section A.4. First, we implement the two-stage differences-in-differences estimator proposed by Butts and Gardner (2021) and Gardner (2021). The two-stage difference-in-differences estimator works by first estimating unit and time fixed effects' contribution to the outcome using only untreated observations. Subsequently, the estimator recovers the predicted residual for all observations in the sample (representing variation in

Figure 4. (Color online) Interstate Medical Licensure Compact Treatment Effect: Coefficient Dynamics



Notes. This figure plots the coefficient dynamics of the 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 time relative to the omitted reference period (i.e., by convention, 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. Licensure information is available at a quarterly frequency, so each period is a quarter. Medicare payment information is available at an annual frequency, so each period is a year. The 95% confidence intervals are indicated by the solid lines. Panels indicate the outcome variables corresponding to Table 5. (a) License. (b) log(*MedService*). (c) log(*MedBenes*). (d) log(*MedPay*). (e) log(*MedStdPay*).

the outcome not explained by fixed effects) and then, uses that adjusted outcome to consistently estimate treatment effects. Gardner (2021) proves that this approach avoids the issues of bias and forbidden comparisons recently raised by Goodman-Bacon (2021) and others.

Second, to alleviate the concern that control variables are jointly affected by the treatments (i.e., that they are potentially bad controls), we replicate our main results omitting those variables. Third, we estimate a simple (canonical) difference-in-differences regression, absent

Table 6. Interstate Medical Licensure Compact Treatment Effect and Urban-Rural Differences

	(1) *LicenseNum*	(2) log(*MedService*)	(3) log(*MedBenes*)	(4) log(*MedPay*)	(5) 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
Adjusted R^2	0.79	0.87	0.88	0.87	0.89

Notes. This table shows the heterogeneous effects of the 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 inclusion of *Physician FEs*. $Compact_{i,t}$ and the outcome variables are defined in the same way as in Table 3. The coefficients of control variables are omitted for the sake of brevity. *Physician FE* refers to the physician fixed effect. The licensure information is available at a quarterly frequency, and Medicare utilization information is available at an annual frequency. Accordingly, we include a year-quarter fixed effect *Yr-Qtr FE* in column (1) and a year fixed effect *Year FE* in the remaining columns. Standard errors are clustered at the physician level, and t statistics are in parentheses. N, no; Y, yes.
***Statistical significance at the 1% level.

any staggering in the treatment, by "nosily" assuming all treated groups are "shocked" at a single point in time, namely the 2017Q2 Compact activation date. Fourth, to alleviate the concern that the treatment effects may be highly heterogeneous across entry cohorts, we show that separately estimating treatment effects by adoption cohort yields a consistent result relative to nonadopter states. Lastly, we replicate Figure 4 employing the interaction weighted method of Sun and Abraham (2021). This estimation only employs never treated states as the control group. When conducting this estimation and producing the associated figures, we once again omit all control variables. The estimates generated via the various methods are all consistent with our main results, as reported in Section 4.1.

4.2.3. Confounding Policy Changes. We also considered whether other concurrent policy changes might confound our estimated impacts from Compact entry. Many concurrent healthcare reforms, such as the CMS Hospital Readmissions Reduction Program, are not state specific, and thus, they will be accounted for by time fixed effects. For our results to be threatened by a contemporary policy change, it would be necessary that the change systematically affect Compact-adopting states in particular and in a manner that coincides with the timing of those states' entry into the Compact. There are two important types of healthcare policy change that may meet these criteria, having been implemented with geographic variation at a subnational level, and thus, they may warrant concern: Medicaid expansion and telehealth parity laws. In Tables A.33 and A.34 in the online appendix, we show that our results are robust to controlling for states implementation of these policies.

4.2.4. Reactions by Rural Physicians. In theory, affected rural physicians can endogenously respond to lost demand by increasing revenues from in-person services. To test whether rural providers compensate in this manner by increasing service volume per patient, we examine the number of services per unique beneficiary and the number of payments per unique beneficiary, contrasting urban and rural providers. We do not observe that these variables significantly increase for affected rural providers as reported in Table A.35 in the online appendix. This is possibly because it is not costless for providers to increase per-patient services; there may be some risk in this strategy. Practices like up coding and ordering excessive diagnostic tests are technically defined as abuse by Medicare. Such activities are actively monitored by the Health and Human Services Inspector General and can lead to licensure revocation or even legal liability. At the same time, the fact that we observe significant negative coefficients on these variables may actually imply that the most profitable rural patients leave their local providers for urban alternatives following their state's Compact entry.

4.3. Mechanism

In this section, we examine two potential mechanisms by which Compact entry and subsequent telehealth service expansion may influence competitive dynamics. We explore these mechanisms directly using patient-level claims data. We construct a panel of patient-year observations, aggregating over all service interactions associated with a particular patient in a particular year. One patient-year observation may therefore capture services rendered by multiple physicians. We aggregate payments based on the type of services patients receive and the urban versus rural location of the associated providers as detailed. We modify the regression in Equation (1) to additionally control for the logged age of the patient, whether the patient is working, and whether the patient holds standard medical insurance. In addition to including year fixed effects, we saturate the model with Metropolitan Statistical Area fixed effects to absorb local characteristics that may affect a patient's medical expenditures. In columns (2) and (4) of Tables 7 and 8, we also incorporate *State* × *Year* fixed effects to focus our estimations on within-state differences following Compact entry. Note that we cannot include physician fixed effects in this estimation because as noted, a patient can receive services from multiple physicians in a given year. We address this concern later via an alternative provider-year regression.

The first mechanism we consider is that urban providers' telehealth services may directly replace rural providers' services. This would be consistent with a substitution effect (Ayabakan et al. 2020), wherein rural patients transition to urban providers as (telehealth-mediated) outpatients. Evidence for this mechanism is illustrated in Table 7, where we distinguish between patient telehealth payments made to urban and rural providers. Column (1) shows that rural patients increase their expenditures to *urban* telehealth providers by 7.6% $(-0.07+0.146)$ following their state's Compact entry. Most importantly, the financial benefits of providing telehealth only accrue to *urban* providers as evidenced in the last two columns, where we find that rural patients significantly *reduce* their telehealth payments to rural providers. This last result indicates that, even within telehealth service consumption, rural patients reallocate their consumption from rural to urban telehealth providers, translating to additional revenue losses for rural physicians.

The second mechanism we consider is that telehealth services may increase a rural patient's propensity to engage with an urban healthcare supplier for *in-person* follow-up services after a telehealth visit. To explore this mechanism, we define gateway visits as the in-person visits with *the same* provider following an initial (remote) telehealth consultancy. Our claim is that telehealth services reduce patients' transaction costs associated with initial consultation and care during posttreatment recovery. To evaluate this mechanism, we calculate patients' annual payments for in-person follow-up services preceded by telehealth visits. We operationalize gateway effect payments as those tied to in-person follow-up visits that happen immediately after the first telehealth visit within a given physician-patient pair. As Table 8 shows, rural patients' reimbursements associated with telehealth gateway effects significantly increase after their states join the Compact yet only if the provider is located in an urban area. Conversely, gateway-visit reimbursements made toward rural providers significantly decreased, consistent with our earlier finding reported in Table 7.

Both of the results support our argument that Compact entry changes the healthcare competition landscape by inducing shifts in telehealth service delivery. To understand the payments from the provider's perspective, we also construct a provider-year panel, wherein each observation includes measures of provider revenue associated with direct telehealth services, in-person follow-up services (the gateway effect), and the sum of the two. In Table 9, we first confirm that total income rises for urban providers yet significantly declines for rural providers, consistent with our other primary results in the paper (columns (1) and (2)). Splitting these payments by service type, we find that rural physicians

Table 7. Interstate Medical Licensure Compact Effects on Patient Telehealth Payments

	(1) $\log(TelePay)^{Urban}$	(2) $\log(TelePay)^{Urban}$	(3) $\log(TelePay)^{Rural}$	(4) $\log(TelePay)^{Rural}$
$Compact_{k,t}$	−0.072*		0.038	
	(−1.666)		(1.357)	
$Rural_k \times Compact_{k,t}$	0.153***	0.211***	−0.193***	−0.187***
	(3.164)	(3.710)	(−3.879)	(−2.772)
Controls	Y	Y	Y	Y
MSA FE	Y	Y	Y	Y
Year FE	Y	N	Y	N
State-Yr FE	N	Y	N	Y
N	435,830	435,827	435,830	435,827
Adjusted R^2	0.08	0.12	0.179	0.21

Notes. This table shows the effect of states' entry to the Compact on patient telehealth consumption based on patient-level claims data (Marketscan). Each observation reflects total telehealth expenditures associated with patient k in year t. $Rural_k$ is a binary indicator that equals one if patient k is located in a rural area and zero otherwise. The coefficient associated with $Rural_k$ is not identified because it is collinear with *MSA FEs*. $Compact_{k,t}$ is a binary indicator set to one if patient k's state has joined the Compact and the Compact is operational as of time t and zero otherwise. $\log(TelePay)_{k,t}^{Urban}$ is the logarithm of patient k's total telehealth payments to urban providers in year t. $\log(TelePay)_{k,t}^{rural}$ is the logarithm of patient k's total telehealth payments to rural providers in year t. Control variables include logged patient age, whether the patient is working, and whether the patient holds standard medical insurance. We omit coefficients associated with controls for the sake of brevity. *MSA FE* refers to MSA fixed effects. In columns (1) and (3), we include year fixed effects *Year FE*, and in columns (2) and (4), we include state-by-year fixed effects *State-Yr FE*. Standard errors are clustered at the MSA level, and t statistics are reported in parentheses. N, no; Y, yes.

*Statistical significance at the 10% level; ***statistical significance at the 1% level.

Table 8. Interstate Medical Licensure Compact Effects on Patient Gateway Payments

	(1) $\log(GatePay)^{Urban}$	(2) $\log(GatePay)^{Urban}$	(3) $\log(GatePay)^{Rural}$	(4) $\log(GatePay)^{Rural}$
$Compact_{k,t}$	−0.158***		0.012	
	(−2.620)		(0.470)	
$Rural_k \times Compact_{k,t}$	0.264***	0.252***	−0.347***	−0.371***
	(2.858)	(2.838)	(−5.815)	(−3.637)
Controls	Y	Y	Y	Y
MSA FE	Y	Y	Y	Y
Year FE	Y	N	Y	N
State-Yr FE	N	Y	N	Y
N	190,816	190,810	190,816	190,810
Adjusted R^2	0.21	0.22	0.30	0.31

Notes. This table shows the effect of states' entry into the Compact on gateway visits based on patient-level claims data (Marketscan). Each observation reflects telehealth expenditures for a patient, k, in year t. $Rural_k$ is a binary indicator set to one if patient k is located in a rural area and zero otherwise. The coefficient associated with $Rural_k$ is not identified in the presence of *MSA FEs*. $Compact_{k,t}$ is a binary indicator set to one if patient k's state has joined the Compact and the Compact is operational as of time t and zero otherwise. A gateway visit is defined as an in-person visit to the telehealth provider following a virtual visit. $\log(GatePay)_{k,t}^{Urban}$ is the logarithm of patient k's total gateway payments to urban providers in year t. $\log(GatePay)_{k,t}^{rural}$ is the logarithm of patient k's total gateway payments to rural providers in year t. Control variables include the logged patient age, whether the patient is working, and whether the patient holds standard medical insurance. The coefficients associated with our controls are omitted for the sake of brevity. *MSA FE* refers to MSA fixed effects. In columns (1) and (3), we include year fixed effects *Year FE*, and in columns (2) and (4), we include state-by-year fixed effects *State-Yr FE*. Standard errors are clustered at the MSA level, and t statistics are reported in parentheses. N, no; Y, yes.
***Statistical significance at the 1% level.

experience a significant decline in telehealth service revenues once their host state joins the Compact (columns (3) and (4)). In the last two columns, we find that urban providers experience a significant increase in revenue because of the gateway effect. The coefficient reflecting the difference in this effect experienced by rural physicians is negative, although statistically insignificant. These findings suggest that the marginal rural patient who is willing to switch from a rural to an urban telehealth provider is generally unlikely to follow up in person with the rural provider. We provide a visual depiction of the effect dynamics in Figure A.2 in the online appendix, where we again observe effects consistent with the assumption of parallel trends.

MarketScan data do not provide an externally linkable physician identifier; each physician is assigned a persistent anonymous identifier throughout the database. Beyond the anonymous identifier, we only have information on the physician's location. As we lack data on hospital affiliation and licensure applications, we cannot use the MarketScan data to undertake many robustness checks, incorporate many control variables, or undertake analyses of heterogeneity based on physician or hospital characteristics. Despite the limitations, these

Table 9. Interstate Medical Licensure Compact Effects on Provider Telehealth Income

	(1) $\log(TotalPay)$	(2) $\log(TotalPay)$	(3) $\log(TelePay)$	(4) $\log(TelePay)$	(5) $\log(GatePay)$	(6) $\log(GatePay)$
$Compact_{i,t}$	0.021*		0.006		0.111***	
	(1.751)		(0.733)		(7.887)	
$Rural_i \times Compact_{k,t}$	−0.099***	−0.072*	−0.157***	−0.132***	−0.032	−0.025
	(−2.668)	(−1.888)	(−5.817)	(−4.800)	(−0.758)	(−0.554)
Physician FE	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N
State-Yr FE	N	Y	N	Y	N	Y
N	534,946	534,939	534,946	534,939	534,946	534,939
Adjusted R^2	0.78	0.79	0.83	0.84	0.52	0.53

Notes. This table shows the effect of states' entry to the Compact on provider telehealth incomes. Each observation reflects total telehealth income by physician i in year t. $Rural_i$ is a binary indicator that equals one if physician i is located in a rural area and zero otherwise. There exist no physicians whose $Metro_i$ changed in our sample period, so the coefficient of $Rural_i$ is not identified given the *Physician FE*. $Compact_{i,t}$ is one if physician i's state has joined the Compact and the Compact is operational as of time t and zero otherwise. $TelePay_{i,t}$ is the total income from direct telehealth services. $GatePay_{i,t}$ is the total income from the in-person follow-up visits by patients that first consult virtually. $TotalPay_{i,t}$ is the summation of $TelePay_{i,t}$ and $GatePay_{i,t}$. No control variables are included. *Physician FE* refers to physician fixed effects. In columns (1), (3), and (5), we include year fixed effects *Year FE*, and in columns (2), (4), and (6), we include state-by-year fixed effects *State-Yr FE*. Standard errors are clustered at the physician level, and t statistics are reported in parentheses. N, no; Y, yes.
*Statistical significance at the 10% level; ***statistical significance at the 1% level.

additional results support the idea that Compact effects manifest via an interstate telehealth channel. First, splitting total telehealth payments received between same-state and out-of-state patients, we obtain the results in Table A.36 in the online appendix, which show that affected urban providers receive additional telehealth revenues only through out-of-state telehealth services. Although rural providers lose payments from both sources following Compact entry, the primary loss is because of a decline in same-state services. Second, Table A.37 in the online appendix shows that incomes from in-person services before the first telehealth visit or unrelated to telehealth services do not significantly increase, thereby ruling out the possibility that such dynamics can explain our main results.

We provide additional support for the role of telehealth visits in driving our results by examining heterogeneity in these effects based on the quality of internet access where patients reside. Rural patients who utilize telehealth services generally require access to high-speed internet. Therefore, rural affected physicians who are based in regions characterized by poorer internet infrastructure should be relatively more protected from telehealth-induced urban competition. Thus, if telehealth services drive our broader results, these rural providers should not exhibit revenue losses following their state's Compact entry. To evaluate this, we draw on the Federal Communications Commission (FCC) broadband coverage annual report for June 2016 through 2018. For each county, the FCC report documents the percentage of rural residents who do not have access to broadband internet service (either fixed or mobile), 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 the rural population lacking access to such services between 2016 and 2018. This measure, *PoorInt*, equals one if the average percentage is greater than the 90th percentile among all counties and zero otherwise. Our cutoff translates to a scenario in which 62% of the rural population has no access to broadband. Although the *PoorInt* indicator increases in value in more rural locations, Table A.38 in the online appendix shows that the coefficient associated with $PoorInt_i \times Compact_{i,t}$ is significant and positive for all Medicare utilization variables. This result is consistent with our expectation; rural providers do not suffer financially from the rise in telehealth competition when their county's patients lack broadband internet access.

Although we provide extensive evidence for the role of telehealth as a driver of our findings, other purely in-person channels may also contribute to the observed revenue shifts. First, some affected physicians are located along state borders. Those physicians may leverage Compact entry to apply for additional licenses and to deliver in-person services in neighboring states. We account for this mechanism in Table A.39 in the online appendix. Affected physicians located along state borders do not apply for new licenses any more frequently, and surprisingly, they tend to experience revenue *reductions* after Compact entry. One explanation for these results is that patients residing on state borders may switch to more distant providers via telehealth.

Second, our results may be influenced by the fact that Compact entry makes it more convenient for physicians to work in person at distant hospitals on a temporary basis, a practice known as locum tenens. We cannot employ our patient claims data to completely rule out or assess the relative magnitude of the influence of such practices because providers are not identified in our Marketscan data. Nonetheless, we *have* established that telehealth expansion is a major contributor.

4.4. Explaining Patients' Preference for Urban Providers

Through their revealed preference, we find that rural patients tend to choose urban providers after telehealth service availability expands. We hypothesize that urban providers experience demand benefits both because they tend to have better telehealth infrastructure and because they are more sought after by rural patients because of their typically higher quality of care. To evaluate these arguments more directly, we incorporate three-way interaction terms into our main regression specification, with estimates reported in the last four columns of Table 6. Here, each additional moderator evaluates a distinct mechanism.

First, we consider heterogeneity in the telehealth readiness of the hospitals with which physicians are affiliated. If the physician's workplace has better telehealth infrastructure, she has a lower fixed cost of adopting and learning about new technologies. Our telehealth readiness measure, $FullTele_{i,t}$, is derived from the American Hospital Association's healthcare IT survey, a voluntary survey that a subset of Medicare hospitals regularly responds to. In the survey, hospitals rate their telehealth implementation on a six-point scale, ranging from "not in place and not considering implementing" to "fully implemented across all units." In our annual physician Medicare payment sample, 6.8% of physicians' working hospitals report that they have fully implemented telehealth services.

The three-way interaction terms are all positive and significant, indicating that affected urban providers receive more financial benefits when their hospitals have better telehealth equipment. The magnitudes indicate that these better-equipped urban physicians service delivery volumes rise by an additional 6.6% and that they receive 3.8% more revenues.[17]

Next, we consider heterogeneity in the quality of physicians' working hospitals. We interact our existing set of variables with $HosRating_{i,t-1}$, the percentage of surveyed inpatients giving the affiliated hospital services the highest possible rating. Consistent with our expectation, the three-way interaction terms are again positive and significant, suggesting that affected urban providers receive more financial benefit when they are capable of providing the highest-quality services. To put these coefficients into context, we compare physicians affiliated with hospitals ranking at the 25th versus 75th percentiles in terms of overall ratings. In our sample, a hospital ranking in the top 25% has at least 76% of its patients reporting a top rating, whereas those ranking in the bottom quarter have at most 67% of their patients reporting a top rating. Therefore, affected urban physicians among the highest-quality hospitals deliver 3.4% more services and receive 3.0% more revenue.[18]

4.5. Welfare Implications

Lastly, we consider the potential positive and negative effects of telehealth expansion on social welfare. Beyond the results we have reported, we also provide suggestive evidence of the impacts of telehealth expansion on quality of care and patient satisfaction in the online appendix. However, because mechanisms are more difficult to assess for those outcomes, we draw no formal conclusions about the net effect of Compact entry on welfare. The welfare effects of telehealth expansion may be positive or negative, as we discuss next.

On the positive side, our results support the argument that Compact entry can address gaps in healthcare demand for rural and underserved areas. Indeed, many rural patients prefer to access urban providers via telehealth services (Tables 7 and 8). Moreover, this fact is true for urban providers that are most capable of delivering high-quality telehealth services. In other words, providers that experience the sharpest increase in demand for their services are those of higher service quality and those with the greatest telehealth readiness (Tables 10 and 11). Rural residents' preference for telehealth-mediated urban providers over in-person rural providers suggests that, before telehealth expansion, rural patients' healthcare options were constrained by travel costs or other barriers to access. In this sense, Compact entry and associated telehealth expansion are welfare improving, at least in the short term.

However, potential welfare losses may arise over the long term for a few reasons. First, demand may concentrate among urban providers, implying that urban providers may gain additional market power. Such a shift would add to concerns about rising concentration in the healthcare market because of mergers and acquisitions. This would be concerning because the healthcare literature documents that market consolidation provides hospitals greater bargaining power with insurers, which in turn, increases service prices for all patients.

Second, urban providers will become busier as they process additional patient flows. The potential exists that, to accommodate the rise in patient volumes, urban providers may reduce their attention to in-person patients. This argument is consistent with the trade-offs proposed by Rajan et al. (2019); telehealth adoption increases total welfare by giving medical services to a larger group of patients, but this is not necessarily a Pareto improvement because patients who live close to the telehealth provider and visit only in person will be burdened by congestion costs and reduced service duration. To evaluate this possibility empirically, we investigate how hospitals' inpatient satisfaction surveys shift following Compact entry in Table A.40 in the online appendix. We find that the percentage of satisfied inpatients at urban hospitals reduces significantly, by 0.46%–0.84%, along various dimensions. Further, when we examine hospital patient flows, we observe that urban hospitals' utilization rates significantly increase after their state joins the Compact (see Table A.41 in the online appendix), which may imply overcrowding.

Finally, if our estimated revenue losses for rural hospitals were to persist into the long term, those hospitals may be forced to downsize (e.g., engaging in divestitures of physical assets and employee layoffs). A reduction in services would likely harm rural patients, particularly those in need of ambulatory and emergency medical services. Although some advocates argue that Compact entry can help rural hospitals to recruit physicians to practice in underserved areas, our results in Table A.41 in the online appendix imply the opposite (i.e., the employment growth rate in affected rural hospitals significantly decreases following state Compact entry). Thus, although there are benefits for many rural patients when telehealth expands, there are several consequences we observe that suggest that some patients may be worse off.

5. Discussion

We have presented a novel, large-scale empirical study of telehealth technologies' effects on competition between urban and rural healthcare providers. Taking this entry event as a 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 evidence that telehealth expansion leads to a systematic shift in patient-provider interactions, consistent with the notion that many rural patients shift their consumption toward urban telehealth providers. In patient-level claim data, we investigate two mechanisms that lead to this shift: a substitution effect and a gateway effect. Lastly, we explore heterogeneity in the advantages experienced by urban providers following telehealth expansion based on their preexisting technology readiness and service quality.

Our work makes several notable contributions. We build most directly on the prior theoretical work by Rajan et al. (2013, 2019). Our empirical results confirm

Table 10. Heterogeneous Interstate Medical Licensure Compact Effects Because of Hospital Telehealth Readiness

	(1) log(*MedService*)	(2) log(*MedBenes*)	(3) log(*MedPay*)	(4) log(*MedStdPay*)
$FullTele_{i,t} \times Metro_i \times Compact_{i,t}$	0.162***	0.078***	0.080*	0.072*
	(2.752)	(2.651)	(1.755)	(1.782)
$FullTele_{i,t} \times Compact_{i,t}$	−0.091	−0.057**	−0.043	−0.045
	(−1.625)	(−2.091)	(−1.003)	(−1.175)
$Metro_i \times Compact_{i,t}$	0.070***	0.045***	0.071***	0.064***
	(4.707)	(4.612)	(5.282)	(5.006)
$FullTele_{i,t} \times Metro_i$	−0.043***	−0.030***	−0.040***	−0.044***
	(−2.624)	(−2.714)	(−2.624)	(−2.651)
$Compact_i$	−0.048***	−0.027***	−0.053***	−0.048***
	(−3.302)	(−2.858)	(−4.057)	(−3.845)
$FullTele_{i,t}$	0.038**	0.033***	0.041***	0.044***
	(2.363)	(2.999)	(2.799)	(2.708)
Controls	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	617,291	617,291	617,291	521,572
Adjusted R^2	0.87	0.88	0.87	0.89

Notes. This table demonstrates heterogeneity in the effect of the Compact entry arising from hospital telehealth readiness. $Metro_i$ is set to one if physician i is located in a metropolitan area and zero otherwise. $Compact_{i,t}$ is set to one if physician i's state has joined the Compact and the Compact has become operational as of time t and is zero otherwise. $FullTele_{i,t}$ is set to one if physician i's hospital has fully implemented telehealth technologies in all units as of year t and is zero otherwise. $\log(MedService)_{i,t}$ 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 payments received for provider i's services in year t after applying deductible and coinsurance amounts. $\log(MedStdPay)_{i,t}$ is the logarithm of (one plus) Medicare payments received for provider i's services in year t after applying deductible and coinsurance amounts as well as geographic standardization. The coefficients associated with our control variables are omitted for the sake of brevity. *Physician FE* refers to physician fixed effects, and *Year FE* refers to year fixed effects. Note that Medicare utilization information is available on an annual basis. Standard errors are clustered at the physician level, and t statistics are reported in parentheses. Y, yes.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

some of their 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. Given that many states have recently passed telehealth parity laws, requiring insurance providers to reimburse in-person and virtual services in the same manner, the urban-rural disparity in health provider financial performance is likely to grow.

Our work suggests at least two important questions that hospital administrators, policy makers, and researchers should strive to address in the coming years. First, given our finding that rural hospitals largely lose out to their urban counterparts when telehealth expands, a natural question is whether and how rural hospitals might survive in the long term. Although rural hospitals draw some small revenue from serving as rural patients' access points to telehealth services, even that revenue source is set to dwindle in the coming years as the quality of rural home internet access continues to improve. To the extent rural provider revenues erode under telehealth, the long-run sustainability of rural community hospitals may become tenuous. Policy makers could allow rural communities to acquire ownership of the hospitals directly and subsidize hospital operations via taxation. Many rural hospitals might manage to survive by cooperating with larger health systems or consolidating a variety of community services under one roof. For example, rural hospitals can provide complementary in-person treatments after rural patients' telehealth consultancies with urban providers.

Second, a pressing question is how urban providers can ensure that quality of care is sustained for face-to-face patients, as their attention shifts toward digitally mediated outpatient services. Recent technological developments in large hospitals, many spurred by the coronavirus disease 2019 pandemic, point to possible paths forward for increased flexibility and performance. For example, recent reports indicate that many large hospitals have introduced inpatient telemedicine platforms, turning rooms and wings into isolation units for infected patients complete with connected devices and audio/visual systems that allow nearby nurses and physicians to monitor patients from elsewhere in the hospital. Thus, many hospitals have instituted systems that enable more efficient care of larger volumes of inpatients. Such advancement in hospital technologies and infrastructure also creates the opportunity for hospitals to assemble geographically dispersed, virtual personal care teams for patients.

Table 11. Heterogeneous Interstate Medical Licensure Compact Effects Because of Hospital Qualities

	(1) log(*MedService*)	(2) log(*MedBenes*)	(3) log(*MedPay*)	(4) log(*MedStdPay*)
$HosRating_{i,t-1} \times Metro_i \times Compact_{i,t}$	0.705***	0.395***	0.537***	0.468**
	(3.074)	(2.646)	(2.609)	(2.401)
$HosRating_{i,t-1} \times Compact_{i,t}$	−0.364*	−0.225	−0.274	−0.222
	(−1.655)	(−1.569)	(−1.383)	(−1.183)
$Metro_i \times Compact_{i,t}$	−0.441***	−0.242**	−0.319**	−0.275*
	(−2.661)	(−2.234)	(−2.138)	(−1.942)
$HosRating_{i,t-1} \times Metro_i$	0.443***	0.291***	0.384***	0.270**
	(3.568)	(3.534)	(3.379)	(2.226)
$Compact_i$	0.217	0.137	0.147	0.113
	(1.366)	(1.313)	(1.022)	(0.829)
$HosRating_{i,t-1}$	−0.409***	−0.204***	−0.310***	−0.260**
	(−3.493)	(−2.624)	(−2.870)	(−2.255)
Controls	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	617,291	617,291	617,291	521,572
Adjusted R^2	0.87	0.88	0.87	0.89

Notes. This table demonstrates heterogeneity in the effect of the Compact entry arising from hospital quality. $Metro_i$ is set to one if physician *i* is located in a metropolitan area and is zero otherwise. $Compact_{i,t}$ is set to one if physician *i*'s state has joined the Compact and the Compact is operational as of time *t* and is zero otherwise. $HosRating_{i,t-1}$ is the overall rating of physician *i*'s affiliated hospital in year $t-1$. $\log(MedService)_{i,t}$ 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 payments received for provider *i*'s services in year *t* after applying deductible and coinsurance amounts. $\log(MedStdPay)_{i,t}$ is the logarithm of (one plus) Medicare payments received for provider *i*'s services in year *t* after applying deductible and coinsurance amounts as well as geographic standardization. The coefficients associated with our control variables are omitted for the sake of brevity. *Physician FE* refers to physician fixed effects, and *Year FE* refers to year fixed effects. Note that Medicare utilization information is available at an annual frequency. Standard errors are clustered at the physician level, and *t* statistics are reported in parentheses. Y, yes.

*Statistical significance at the 10% level; **statistical significance at the 5% level; ***statistical significance at the 1% level.

6. Limitations and Conclusion

Our work is subject to a number of empirical limitations. First, we are unable to directly evaluate all of the mechanisms that may contribute to the shift in revenues from rural to urban providers after Compact entry, mainly because we lack a fully identified insurance claim database. Although we can confirm and demonstrate the contribution of telehealth expansion, we are not able to quantitatively compare the importance of telehealth services relative to in-person visits. Second, our sample provides comprehensive data on roughly two years of activity following states' Compact entry, and it coincides with a period of rapid telehealth market growth. Our sample is thus unable to speak to long-run effects. Although we provide some discussion of long-run implications in Section 4.5, an additional empirical study is warranted as more data accrue. Third, our available data enable us only to proxy physician quality using affiliated hospital ratings in Section 4.4; future work should look to leverage more granular, physician-level quality information.

Fourth and last, although our work provides a broad consideration of telehealth expansion and its implications for healthcare competition across the urban-rural divide, our analyses do not account for the recent growth of direct-to-consumer (D2C) telehealth offerings (Jain et al. 2019). Many digital services have begun offering online prescriptions in recent years (e.g., contraception, erectile dysfunction, and hair loss). Further, several purely digital platforms, like Teladoc and AmWell, have begun to offer a broader range of direct-to-consumer medical services without any involvement of hospitals or clinics. Additionally, some of these services are also integrated with retail pharmacy networks, such as CVS and Walgreens, to provide brick-and-mortar access points. These developments imply that significant disruption may be on the horizon for traditional medical providers, urban and rural alike. Future work should also consider the expansion of D2C telehealth offerings to understand the effect these entrants have on incumbent providers.

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Endnotes

[1] After several states passed the law to join the Compact, it became operational in April 2017.

[2] 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 (e.g., as a result of lobbying by large healthcare-provider networks). Accordingly, we evaluate self-selection concerns by verifying that observed geographic, economic, and healthcare market characteristics are not predictive of state entry into the Compact in Section A.1 in the online appendix.

[3] We provide more direct evidence that telehealth service expansion is a contributing mechanism in subsequent analyses based on our healthcare claims data.

[4] See the *Wall Street Journal* article "A Cancer Patient's Brutal Commute" (https://www.wsj.com/articles/a-cancer-patients-brutal-commute-11626129627, last accessed July 14, 2021).

[5] 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, last accessed January 14, 2021).

[6] For example, the Arizona Medical Board reminds physicians that "[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."

[7] See "Physician Licensure Application Fees and Timelines by State" from Medicus Healthcare Solutions (https://medicushcs.com/resources/physician-licensure-application-fees-and-timelines-by-state, February 2019).

[8] See the article "Physician Licensure Barriers to 21st Century Healthcare" from the American Telemedicine Association (http://telemedicinenews.blogspot.com/2012/02/ata-highlights-licensing-barriers.html, February 2012).

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

[10] See the public hearing transcript of Nebraska LB61 in 2017 (https://www.nebraskalegislature.gov/FloorDocs/105/PDF/Transcripts/Health/2017-01-19.pdf).

[11] https://www.cms.gov/openpayments/data.

[12] We consider the prior two years of license history because drug companies sometimes fail to report all state licenses that a physician holds and because a state license is typically renewed every one or two years. Note that our results are robust to the use of alternative windows (e.g., prior half year, year, or five years).

[13] There is no unified identifier between the two databases. We, therefore, match physicians based on first name, last name, and middle initial, and we require that the primary operating state is reported in the payment information. When the matching criteria resulted in duplicates, we manually searched for the doctor's information online to identify the correct match.

[14] Our data are based on the Physician Compare database, which represents all physicians with the CMS. Again, we retain physicians with nonmissing 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. Among them, 620,795 have payment information in the Provider PUF database.

[15] As a point of comparison, over 99% of urban patients also utilize urban physicians for telehealth services.

[16] $PastAction_{i,t}$ is a publicly available indicator for previous misconducts, which can reduce physician revenues. We note that roughly 9 of every 1,000 physicians have a disciplinary action against them, implying that variance in the measure is somewhat limited. The consequence of a lack of variation is that the associated coefficient may be estimated imprecisely.

[17] These numbers are calculated by summing over all terms involving *FullTele*. For example, $6.6\% = 0.162 - 0.091 - 0.043 + 0.038$ in column (1).

[18] These numbers are generated by summing over all terms involving *HosRating* and multiplying the summation by $0.76 - 0.67$. For example, $3.0\% = (0.537 - 0.274 + 0.384 - 0.310) \times 0.09$ in column (3).

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