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Delivering Healthcare Through Teleconsultations: Implications for Offline Healthcare Disparity

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Abstract. Teleconsultations allow patients to search for, receive, and pay for medical consultations virtually. With remote diagnosis and treatment capability, teleconsultations have been proposed as a potential solution to the long-standing social problem of geographic disparity in healthcare. Although this sounds promising, unforeseen frictions could suppress the virtual flow of healthcare. It is unclear, then, whether teleconsultations actually mobilize healthcare to underserved regions. To advance our understanding, we first empirically investigate whether teleconsultations generate a virtual flow of healthcare to mitigate geographic healthcare disparity. Second, we examine whether social, information, and geography frictions are present in the virtual healthcare flow. To this end, we curate unique data capturing regional offline health resources and various regional characteristics and match them with teleconsultation instances over 10 years (2006–2015). Our exponential random graph model analysis provides encouraging empirical evidence that teleconsultations connect physicians in resourceful regions and patients in underserved areas—a desirable direction that can alleviate geographic healthcare disparity. However, we also find that various frictions are present. For instance, social and information frictions, such as cultural and linguistic differences and limited media coverage, suppress the supposedly free flow of teleconsultations across regions. Furthermore, although teleconsultation is anticipated to spark long-distance healthcare, we find that teleconsultations are less likely as the regions between patient and physician become farther apart. We examine two plausible mechanisms that contribute to the observed geography friction: (1) a low-information bandwidth of a teleconsultation channel and (2) the financial constraint of rural patients. Supplementary analyses using granular data (fees, physician ranks, and illness types) provide corroborating evidence for the proposed mechanisms.

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Keywords: telemedicine • information technology • geographic disparities in healthcare • exponential random graph model

Your zip code shouldn't determine how long you live, but it does.

—Dr. Anthony Iton, the California Endowment's senior vice president for Healthy Communities (quoted in Tash (2016))

1. Introduction

Geographic healthcare disparity is a long-standing social problem across the globe. Although half of the world's population lives in rural areas, only 23% of healthcare workers are deployed in rural areas (United Nations 2012). For instance, in the United States, urban areas have approximately nine times more medical specialists than do rural areas (Meit et al. 2014). As a result, rural patients in the U.S. travel about three times farther to see medical specialists than those living in metropolitan areas (U.S. Department of Health and Human Services 2013). Despite governments' constant efforts, this problem has been challenging to fix, because urban cities offer more attractive social, cultural, and professional environments to health professionals and their family members (United Nations 2012, World Health Organization (WHO) 2013).

Recently, teleconsultation service has opened up an exciting opportunity to improve health resource disparity without physically relocating healthcare providers. Teleconsultation is one type of telehealth service that allows patients to get medical consultations virtually. According to WHO, telehealth is broadly defined as "*the delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of advancing the health of individuals and their communities*" (quoted in WHO Global Observatory for eHealth (2010), p. 9, italics in original). The common goal of telehealth is to boost long-distance healthcare by enabling patients and healthcare providers to communicate through technologies.

With its capability of long-distance diagnosis and treatment, teleconsultation is proposed as a solution to increase healthcare access to underserved areas. Although this sounds promising, it is unclear whether teleconsultation actually augments healthcare access to underserved regions, because unforeseen obstacles could curb the virtual flow of healthcare. This study aims to advance our knowledge of how teleconsultation mobilizes healthcare across locations. Specifically, the goal of this study is twofold. First, we investigate how teleconsultations virtually mobilize healthcare across regions. This analysis brings an important social implication for the role of teleconsultations in alleviating offline healthcare disparity. Second, we examine factors that create frictions in the virtual healthcare flow. Understanding the obstacles can help healthcare providers and policy makers devise a way to enhance teleconsultations' reachability.

For the empirical investigation, we construct a novel longitudinal data set that captures each region's offline healthcare resources and teleconsultations across these regions (2006–2015). We further match them with a rich set of individual region and region-pair characteristics to understand the drivers of and obstacles to teleconsultation flow. During our empirical period, a total of 119,820 teleconsultations took place between 32,219 patients and 4,351 physicians. To empirically analyze the factors that influence cross-regional teleconsultations, we conduct a series of exponential random graph model (ERGM) analyses. ERGM is a stochastic network modeling approach that offers several advantages in modeling network interactions over alternative statistical models such as regressions.

Our analysis reveals encouraging evidence that teleconsultations indeed generate virtual healthcare flow from resourceful to underserved regions—a desirable direction to attenuate offline healthcare disparity. This finding highlights the exciting capability of teleconsultations to virtually distribute slack resources. However, alongside this encouraging evidence, we also find that several factors hamper teleconsultation flows. In particular, we find that social and information frictions, driven by cultural and linguistic differences and limited media coverage, suppress the free flow of teleconsultations across regions. Furthermore, although teleconsultations offer the capability to connect physicians and patients regardless of their distance, we find that the farther apart two regions are, the fewer the teleconsultations that occur between them. We explore two plausible mechanisms that may drive the observed geography friction: (1) a low-information bandwidth of a teleconsultation channel and (2) the financial constraint of patients in underserved areas. Additional analyses using granular data (fees, physician ranks, and illness types) provide corroborating evidence to the proposed mechanisms.

The findings bear useful implications for practice. First, to improve geographic health disparity, government agencies have increased their funding for teleconsultations. Despite high interest in teleconsultations, to the best of our knowledge, few studies have examined their societal value. Although the societal value might seem conceptually obvious, verifying it empirically is important. Previous studies found that people often use technology in an unexpected way, resulting in unintended consequences (e.g., Watson et al. 1988 and Piccoli and Ives 2003). Hence, the true impact of the technology depends on how people actually use it (Zammuto et al. 2007). The extant literature on this topic is largely based on anecdotal or limited evidence. The result of our analysis based on large-scale data provides compelling evidence that teleconsultations expand the healthcare supply in underserved regions by connecting physicians in resourceful regions with rural patients. Second, we find that enhanced physical accessibility increases teleconsultations between regions. One might think that technology infrastructure (e.g., the broadband service) would be sufficient to enable teleconsultations, yet our finding suggests that limited physical mobility can prevent isolated regions from benefiting from it. Local governments and hospitals may work together to improve a public transportation system or provide an alternative mode of transportations such as hospital shuttle buses. Third, our finding suggests that cheaper teleconsultations tend to reach farther. To increase the participation of rural patients, policy makers may consider offering subsidies for rural patients or enforce price transparency among teleconsultation platforms to make patients' search for affordable services easier. Also, teleconsultation platforms may recruit physicians who are willing to charge affordable fees for rural patients. Fourth, the observed information friction suggests that teleconsultations may be more widely utilized with providers' and governments' concerted efforts to make the service known. For example, they may circulate brochures that list available teleconsultation services by illness, information about physicians, and fees, among other things, and share patient experiences in these services. Finally, to reduce the language barrier, we suggest that teleconsultation platforms mandate physicians to indicate the dialects and languages they can speak (including the official national spoken language).

The remainder of this paper is organized as follows. In Section 2, we theorize on teleconsultations' role in geographic healthcare disparity and the potential frictions of cross-regional teleconsultations. In Sections 3 and 4, we describe our empirical context and model, respectively. In Section 5, we present the results of our ERGM analysis on (1) how teleconsultations mobilize healthcare across locations and (2) frictions to the virtual healthcare flow. We present the results of robustness checks and supplementary analyses in Section 6. In Section 7, we discuss our findings and conclusions.

2. Teleconsultation and Geographic Healthcare Disparity

2.1. Geographic Healthcare Disparity

Healthcare disparity refers to systematic differences in healthcare access and health status of different population groups (WHO 2017). Although disparities may occur along various dimensions (age, gender, income, ethnicity, etc.), geographic disparity refers to health inequities driven by geographic disadvantages.

The geographic disparity is a global problem. Substantial healthcare gaps exist between as well as within countries. According to the World Health Organization (2011), there is a 36-year gap in life expectancy between countries: a child born in Malawi can expect to live for only 47 years, whereas a child born in Japan could live for as long as 83 years. It is alarming that such a discrepancy persists even after controlling for biological and genetic differences.

A considerable geographic gap also exists within countries. Although it is more severe in developing countries, industrialized countries are not immune to the problem. For instance, there are only 30 medical specialists per 100,000 people in rural communities in the United States, compared with 263 specialists per 100,000 urban residents (Warshaw 2017). A study by the University of Minnesota School of Public Health (Hung et al. 2017) illustrates a rural healthcare deficit. The study finds that 45% of rural counties in the United States did not have any hospitals with obstetric services between 2004 and 2014, and 9% of counties lost all hospital obstetric services within the county during the study period. As a result, by 2014, 54% of rural communities lacked obstetric services. This figure equates to 2.4 million people of reproductive age living in counties without hospital obstetric services. The study further reports that some rural residents needed to travel 200 miles as a result of this supply shortage.

As noted, insufficient physician supply necessitates that rural residents travel far, but these long distances bring additional hurdles to rural healthcare. Traveling out of town demands a lot of time and energy. It may mean taking hours or a day off from work for those living in remote areas. Challenging transportation environments (e.g., poorly marked roads and limited public transportation) make it even harder (Goins et al. 2005). Besides, long travel distances cause extended wait times for emergency services, endangering patients who need timely interventions. For instance, roads to and from rural areas are often closed because of snow, and in such cases, the only way out for emergency care is via air transportation, which is extremely expensive and hard to get. In brief, geographic disadvantages obstruct rural patients from receiving adequate medical care. As a result, rural patients tend to exhibit higher morbidity and mortality rates than urban patients (Knudson et al. 2016, Centers for Disease Control and Prevention 2020).

2.2. Teleconsultations: Opportunity to Virtually Mobilize Healthcare

Telehealth is an umbrella term that covers a broad spectrum of healthcare services delivered through information and communication technologies (WHO Global Observatory for eHealth 2010). Telehealth includes services that involve physicians as well as those that do not (e.g., telepharmacy, telenursing, and telemonitoring). The rather broad definition of telehealth by WHO is intentional, because the field is evolving rapidly. Although the history of telehealth can be traced back to the late 19th century when electrocardiograph data were transmitted over telephone wires (Patterson 2005), the modern form of telehealth started in the 1960s, led by the military and space technology sectors. Recent advancements in technology, particularly the arrival of the internet, fueled the field of telehealth as the availability and affordability of information technologies increased dramatically (WHO Global Observatory for eHealth 2010). The term "mobile health" is also often used to refer to the telehealth services supported by mobile communication devices such as smartphones, tablets, and wireless patient monitoring systems (Weinstein et al. 2014).

Teleconsultation, the focus of this study, is a subtype of telehealth services that enable physicians to connect with patients to make a diagnosis, guide treatments, and provide support at a distance. Teleconsultations may be offered in multiple ways (i.e., email, texts, audio, or visual technologies in an asynchronous and synchronous manner) and across various illnesses. Teleconsulting for nonsurgical illnesses such as mental illnesses would be an easier transition than surgical illnesses (e.g., orthopedic illnesses). Still, although physicians cannot conduct

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actual surgeries using teleconsultation, physicians may use it to provide information about upcoming surgeries or conduct checkups after surgery. In fact, in our empirical setting, we observe that a nonnegligible portion (~ 40%) of teleconsultations are to treat surgical illnesses. The key distinguishing feature of teleconsultations from face-to-face medical consultations is that patients and physicians do not need to meet in person. For a face-to-face consultation, patients need to spend time, effort, and money to travel to meet a physician. However, for teleconsultation, patients can conveniently receive medical care in the comfort of home instead of traveling hours or days to a hospital and waiting for an appointment. In our empirical context, for instance, a patient can simply visit the teleconsultation platform, search for the right physician, schedule with the physician, and receive a teleconsultation in any convenient place.

Because of this convenient travel-free feature, teleconsultations are believed to be a promising solution to geographic healthcare disparity (WHO Global Observatory for eHealth 2010). Patients residing in resource-poor regions have insufficient local healthcare resources; consequently, they have needs to seek medical care from outside physicians. By contrast, physicians in resourceful regions are likely to have some slack resources that can possibly be used to meet rural patients' unmatched needs. Previously, such needs were difficult to meet because patients in need had to travel hundreds of miles to meet physicians in resourceful areas (Dorsey et al. 2013). Teleconsultation makes it much easier by enabling patients to bypass a long-distance trip to a physician's office. By making healthcare more accessible, teleconsultations offer the potential to improve the disparity of health outcomes across resourceful and underserved regions.

Based on this exciting possibility of virtual care, government agencies have supported telemedicine initiatives to alleviate geographic healthcare disparity. With governments' support and rising demand for virtual care, the global telemedicine market size is projected to reach $298.9 billion by 2028 (Grand View Research 2021). In line with this reasoning, we expect that teleconsultation services would facilitate virtual healthcare delivery from resourceful to underserved areas.

2.3. Social, Information, and Geography Frictions to Teleconsultation Flows

Although teleconsultations offer exciting potential to mobilize health resources across regions virtually, they are not completely frictionless. In particular, previous studies provide descriptive evidence of technological barriers: the lack of high-speed bandwidth and equipment may hinder the implementation of teleconsultations (Stroetmann et al. 2011, Levine et al. 2014, Lycett et al. 2014). In addition, regulatory barriers, such as restricted physician licensing (Jang-Jaccard et al. 2014), are found to curb teleconsultations' expansion. For instance, in the United States, a physician license's geographic restrictions[1] blocks the flow of teleconsultations across states, although such teleconsultations are technologically feasible.

Once the technology and regulatory frictions are cleared, it might seem likely that patients would fully leverage the advantages of virtual care and reach out to a global set of healthcare providers who can provide them the best care. However, previous studies have shown that most patients are unable and often unwilling to make a rational choice in selecting a healthcare provider. Instead, a patient's choice of a healthcare provider is heavily influenced by social, information, and geography frictions (Victoor et al. 2012). For instance, it is consistently found that patients regard an interpersonal factor as more important than objective quality measures. Patients prefer physicians they personally click with (Schnatz et al. 2007, Kolstad and Chernew 2009) and can communicate with without difficulty (Schneider and Epstein 1998, Fotaki et al. 2008). Although patients indicate that they will use objective quality measures when selecting healthcare providers, they are later found to rely heavily on interpersonal factors and on their family/friends' prior experience (Kolstad and Chernew 2009, Sinaiko 2011). Or many patients use only geographical considerations in their choice of healthcare provider, going to those who are easily accessible through public transportation (Haynes et al. 2003, Exworthy and Peckham 2006).

Similarly, a patients' choice of teleconsultation providers may be influenced by social, information, and geography frictions. Although technology and regulatory frictions are well studied and actions are actively underway to reduce them (LeRouge and Garfield 2013), practitioners are recognizing that frictions in these other dimensions are also slowing down the broad adoption of teleconsultations (Correa and Pavez 2016, Kruse et al. 2018), which may suppress the supposedly free flow of teleconsultations across regions. Consequently, in this study, we aim to advance our understanding of the less understood social, information, and geography frictions.

First, social friction may hinder teleconsultations. Prior studies found that one key factor that patients consider in choosing a healthcare provider is interpersonal relationships (Victoor et al. 2012). Patients prefer a provider with whom they can easily converse and make psychological connections (Kolstad and Chernew 2009). Similarly, we expect that patients would regard social factors as important in choosing teleconsultation providers. Patients are likely to feel more comfortable interacting with physicians from the same cultural background, as cultural similarity reduces uncertainties in communication (Krauss and Fussell 1990). Patients are also likely to prefer physicians who use the patients' own dialects, because physicians and patients can rely on fewer behavioral clues during teleconsultations (e.g., body language, facial expressions). In sum, because cultural and language differences add uncertainty to interpersonal relationships, they may serve as social frictions and suppress virtual healthcare flow across regions.

Second, information friction may also suppress teleconsultations. Prior studies found that socially isolated patients tend to have limited information access, and their unawareness of healthcare services significantly restricts their ability to seek adequate medical care (Periyakoil 2010, Correa and Pavez 2016). Similarly, it is possible that patients' unawareness of teleconsultation services may restrict their ability to seek teleconsultations. In such a setting, where patients do not necessarily have prior face-to-face relationships with physicians, they rely on media information. Because patients tend to choose physicians they know and trust (Mosadeghrad 2014), patients are likely to pick physicians about whom they have more information. Hence, limited media coverage between regions may decrease information exposure and interregional teleconsultations.

Third, geography friction may prevail in teleconsultations. Offline, geographic proximity plays a fundamental role in human interactions. Abundant evidence from offline settings shows that people are more likely to form relationships with nearby others because geographic proximity increases chances to meet, which in turn increase the probability of forming ties (e.g., Festinger et al. 1950, Kraut et al. 1999, Hampton and Wellman 2000, and McPherson et al. 2001). With the advent of advanced telecommunication technology, particularly the internet, some scholars argue that the world will become flat (Friedman 2007) and physical distance is dead (Cairncross 2001). Their arguments are theoretically appealing because the internet, indeed, has the technical capability to easily connect people over distance: as long as broadband infrastructure is in place, connecting with someone next door and someone across continents takes roughly the same effort.

Although teleconsultations are meant to enable distance care, long-distance teleconsultations may be less preferred than nearby ones. One possible reason is the low information bandwidth of a teleconsultation channel. Because teleconsultations do not support rich information gathering through "touch-and-feel" interactions, patients might anticipate potential face-to-face follow-up with the teleconsultation provider, or they might anticipate needing laboratory tests or medical imaging tests (e.g., X-rays, MRI). Because most ancillary service networks of a healthcare provider (e.g., radiology, laboratory tests, physical therapy, and behavioral therapy) are located in physical proximity, nearby teleconsultation providers are likely to be more convenient for patients. Hence, even though teleconsultations can technically connect any physicians regardless of distance, patients may still prefer nearby physicians or those in easily accessible locations through public transportations.

Another potential reason long-distance teleconsultation may be less preferred is that rural patients face financial constraints. Along with the lack of healthcare supply and transportation difficulty, rural residents' financial constraints are a key obstacle to adequate healthcare (Periyakoil 2010). Across the globe, rural communities tend to be poorer and have more uninsured residents and higher unemployment rates, leading to less access to healthcare (WHO 2013). Such urban-rural income inequality is severe in our empirical context: the per capita income of urban households in China is about three times that of the rural household (Jain-Chandra et al. 2018). Although less severe, income inequality prevails in developed countries, too.[2] Consequently, even though it might be technically feasible to reach out to physicians in distant locations, rural patients may not be able to afford high-quality physicians' consultation fees.

In sum, although teleconsultation offers patients the technical capability to reach out to a global set of physicians with only a few clicks, several friction factors may prevent patients from utilizing its full potential.

3. Research Context and Data

3.1. Geographic Healthcare Disparity in China

As in the United States (Meit et al. 2014) and many other countries (United Nations 2012), healthcare resources are not evenly distributed across China. Medical professionals are highly concentrated in metropolitan cities such as Beijing and Shanghai, and rural residents in China have significantly lower access to primary and specialized healthcare services. As a result, almost 10% of Chinese rural residents travel for several hours to receive basic medical care, compared with only 1% of their urban counterparts (Dollar 2007). This imbalance in health resources leads to further disparity in many important health outcomes. For instance, rates of vaccine-preventable diseases, such as measles, are five to six times higher in the western provinces in China (rural areas) than the eastern provinces (urban areas) (WHO Global Observatory for eHealth 2010). Such health outcome disparities can be improved by providing rural residents with essential, inexpensive healthcare services. A severe geographic imbalance in health resources has even created a black market for appointment tickets for physicians, which further limits rural patients' access to health resources because urban patients tend to have higher incomes than rural patients.[3]

3.2. Teleconsultation Service

The teleconsultation service we study in this paper is offered by a large online healthcare platform in China. This platform launched in September 2006, and the number of participants has grown dramatically ever since. The platform offers various services, including a physician directory, an illness library, patient communities, teleconsultation, and electronic prescription services. The physician directory makes it easier for patients to locate and contact physicians, providing information such as physicians' medical specialties, affiliated hospitals, job titles, locations, pictures, and contact information. The illness library provides comprehensive information about common symptoms and recommends treatment plans for various diseases. Patient communities offer patients and their families a virtual place to share treatment information and receive emotional support. Such offerings provide *indirect* medical benefits to patients by offering rich, up-to-date information about their illnesses.

By contrast, teleconsultation services provide *direct* medical care to patients by enabling them to receive physicians' consultations remotely. Participating physicians span a broad spectrum of specialties such as orthopedics, internal medicine, otorhinolaryngology, oncology, and psychiatry, among others. This service works as follows. First, a patient visits the healthcare platform; searches for a physician by specialty, hospital, and consultation fee; and then chooses the right physician. Second, the patient places a request for a consultation during a specific time frame. On this page, the patient provides personal information such as age, gender, phone number, and current symptoms. The patient can also upload supporting documents such as previous diagnosis reports, medical images, and pictures. Third, the patient pays for the requested consultation and then receives a confirmation with the exact time of consultation. Fourth, at the scheduled time, the platform transfers the physician's phone call to the patient. Once connected, the physician discusses the patient's symptoms and makes treatment recommendations. Figure 1 illustrates the process. Participation in the teleconsultation service is optional for physicians. Participating physicians conduct teleconsultations in their off-hours for extra income, and they are allowed to set their fees. In general, physicians set teleconsultation fees similar to those of their offline consultations. The physical distance between a physician and a patient does not affect the consultation fee, and the healthcare platform does not use a recommendation system to suggest physicians to patients. There was no insurance reimbursement for the teleconsultation service during our study period.

3.3. Data

To empirically assess how teleconsultation service delivers healthcare across regions, we have consolidated a unique longitudinal data set that spans 10 years (2006–2015) by combining (1) teleconsultation instances, (2) offline health resource information, and (3) various characteristics of regions at a region-pair and at an individual-region level.

The first component of our data set, teleconsultation instances, contains rich information about every physician-to-patient teleconsultation that happened between the service's launch in October 2006 and May 2015. For each teleconsultation, we collected (a) the location of a physician and a patient, (b) date of each consultation, (c) illness of a patient, and (d) physician characteristics (e.g., an affiliated hospital, job title). As shown in Figure 2, the participation of patients and physicians in the teleconsultation service has increased significantly; over those 10 years, 119,820 teleconsultations occurred between 32,219 patients and 4,351 physicians. Furthermore, participants in the teleconsultation service have geographically expanded considerably over time. Figure 3 presents the visualization of the cross-regional teleconsultations in 2007 and 2015, respectively. Whereas 56 regions (mostly urban) participated in 2007, 221 regions used the service in 2015. Cumulatively, physicians and patients in 319 regions (95% of all regions) participated in the service during our empirical period.

The second component of our data set, offline health resource information, contains an annual stock of medical professionals and facilities in each region. To capture offline health resources in terms of medical professionals, we collected an annual count of physicians for each region over the same 10-year period of the teleconsultation data using the 2006–2015 volumes of the *China Statistical Yearbook of Health and Family Planning* (published by the Peking Union Medical College Press). To account for the different population sizes of regions, we calculate the per capita number of physicians for each region by dividing each region's total physician count by its population. To capture offline health resources in medical facilities, we collected the total number of hospital beds in each region and normalized it by each region's

Figure 1. Teleconsultation Process

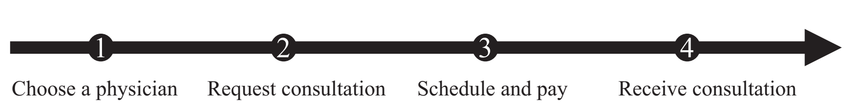
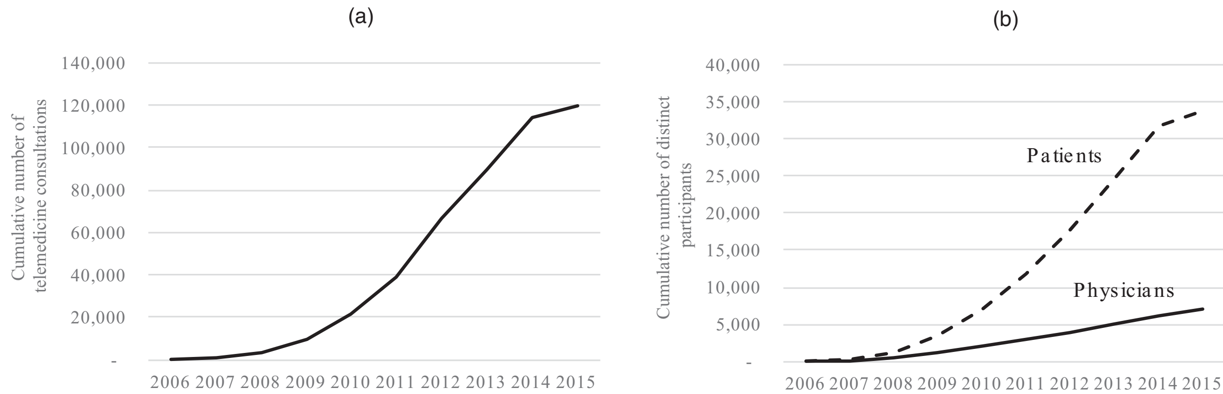


Figure 2. Teleconsultation Activities (2006–2015)



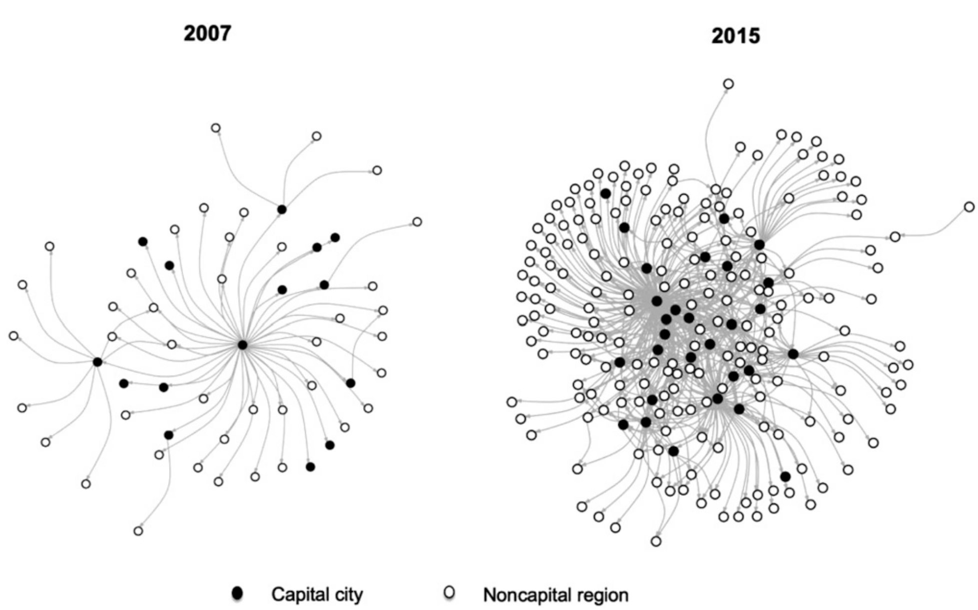
Notes. The data points for 2006 and 2015 are based on partial year. Our data span from October 2006 to May 2015.

population. As expected, offline health resources are highly concentrated in metropolitan cities such as Beijing, Shanghai, and Guangzhou. For instance, there are 932.30 medical professionals per 10,000 Guangzhou city residents, compared with a mere 1.78 per 10,000 residents in Huangnan Tibetan Autonomous Prefecture, a rural region.

The last component of our data set is region characteristics. Various region and region-pair characteristics may influence teleconsultations. To incorporate them into our model, we collected the following: For each region, we collected information on its population size, gross domestic product (GDP), latitude/longitude, jurisdiction, internet penetration ratio, offline insurance restriction, and to which cultural and dialect group it belongs. The annual population, GDP, and internet penetration ratio information was obtained from the 2006–2015 volumes of the *China Statistical Yearbook*, published by the National Bureau of Statistics of China. For each region's internet penetration ratio, we collected an annual number of households with broadband service and divided the number by its total number of households. We collected each region's latitude and longitude information and its jurisdiction boundary information from the Geocoding API by Google.

To capture the effect of the cultural difference on teleconsultations, we identified each region's cultural origin. According to Yuan and Chen (2014), a set of areas may be grouped into a subculture group if they share a similar history, art/architecture style, and

Figure 3. Teleconsultation Flows Across Regions



governance structure. We used this subculture classification to measure cultural dissimilarity between regions. We also utilized 23 linguistic subgroup categorizations based on Liu et al. (2015) to label 336 regions with their linguistic origin. Although Mandarin is the official standard language in China, regions that belong to different linguistic origins may have some remnants of dialects (e.g., accents). On the basis of the linguistic origin label, we later create a dummy variable, a linguistic barrier that captures whether a region pair belongs to a different linguistic origin.

We also collected information about the offline health insurance policy to tease out its effect on teleconsultation patterns. China has a national health insurance system that is under the country's social insurance plan. Although health insurance provides nationwide coverage for all residents in China, the insurance enforces unfavorable insurance reimbursement rates for some rural patients when they meet nonlocal physicians. We do not expect that this offline insurance restriction directly impacts teleconsultations, because telemedicine service was not covered by insurance during our empirical period. Yet such offline insurance restrictions may influence the patients' decision to use teleconsultations if they complement teleconsultations with offline consultations. To capture this potential effect from offline insurance restriction, we used the 2005–2016 volumes of the *China Statistical Yearbook* to collect data about the proportion of residents who are subject to the insurance restriction for each region.

Furthermore, for each region pair, we collected media coverage information to measure information friction between regions. To collect these data, we went through the following process. First, we logged all radio and TV channels in China during our empirical period. Second, for every TV and radio channel, we assembled its wavelength information to figure out each channel's coverage area. Third, based on each channel's coverage area, we calculated how many channels each region pair shares. The number of shared TV and radio channels is used as a proxy to measure the degree of common information exposure between regions. Whereas some channels are broadcasted nationally, others' signals only reach up to a few vicinity regions, creating regional variations in information exposure. Finally, to control the effect of offline physical accessibility on teleconsultations, we collected the annual availability of public transportation options between regions. In particular, we collected annual high-speed train and domestic flight availability for all 112,560 region pairs (336×335 regions) in our data set.

In addition, for our supplementary analysis of offline patient flow, we collected additional sets of data, including the offline cross-province patient ratio from the Ministry of Human Resources and Social Security of the People's Republic of China and the offline cross-region patient ratio from a large Beijing hospital. We describe these data later in Section 6.

4. The Empirical Model

We first provide an overview of ERGM in Section 4.1 and then describe details of the teleconsultation network and network model variables in Sections 4.2 and 4.3.

4.1. ERGM

We use ERGM to analyze the interaction patterns of the teleconsultation network. ERGM is a stochastic network modeling approach based on the exponential-family theory for specifying the probability distribution for a set of random graphs or networks (Snijders et al. 2006, Robins et al. 2007, Krivitsky 2012, Lusher and Robins 2013). ERGM allows researchers to examine the underlying social processes that lead to the emergence of the observed network structure.

ERGM offers several advantages in modeling network interactions over alternative statistical models, such as regression models. First, ERGM incorporates the interdependence among network ties. Observations in network data are not independent of each other, as one node may be involved in multiple dyads, violating the independent and identically distributed variables (IID) assumption of regression models. ERGM explicitly models such dependence, so it does not require the IID assumption. Second, ERGM captures the self-organizing processes of network tie formation. A network tie may emerge because of other preexisting ties. Common examples of such self-organizing (endogenous) network properties are reciprocity ("returning a favor") and triad closure ("a friend of a friend is more likely to be a friend"). By allowing the probability of a tie to be dependent on other ties' status, ERGM allows researchers to capture the self-organizing property of networks, if there is any. As a result, previous studies report that ERGM tends to produce more conservative estimates than regression models (e.g., Robins et al. 2007 and Kim et al. 2016).

The general functional form of ERGM for a valued network (valued ERGM) is as follows. Let Y denote an adjacency matrix of a random network, and let $\mathcal{Y}$ denote a set of all obtainable networks. Denote by y a realized network and by n the number of nodes. Ties are represented in an $n \times n$ adjacency matrix Y, where Y_{ij} represents an interaction strength between nodes i and j without a priori upper bound. The distribution of Y can be parameterized in the following form: For $y \in \mathcal{Y}$,

$$P_{h,g}(Y = y; n, \theta) = \frac{h(y)\exp(\theta^T g(y, X))}{k_{h,g}(\theta)}, \quad (1)$$

where $g(y, X)$ is a row vector with q model covariates that are constructed based on y and a matrix X. The matrix X contains additional information about n nodes. Model covariates may include individual-level, dyad-level, or higher-level network structural covariates. The parameter θ is a column vector with q unknown model coefficients to be estimated. The estimated parameter θ explains the characteristics of network members and network structures that are associated with the probability of the observed tie strength. The function $h(y)$ determines the basic shape of the ERGM distribution, and $h(y) = \prod_{(i,j)\in Y}(y_{i,j}!)^{-1}$ in ERGM for a valued network (Krivitsky 2012). The denominator in (1) is a normalizing constant defined by

$$k_{h,g}(\theta) = \sum_{y\in\mathcal{Y}} h(y)\exp(\theta^T g(y, X)), \qquad (2)$$

which represents the sum of the numerator over all possible networks with n nodes. It ensures that the probability of observing network y is bounded between 0 and 1.

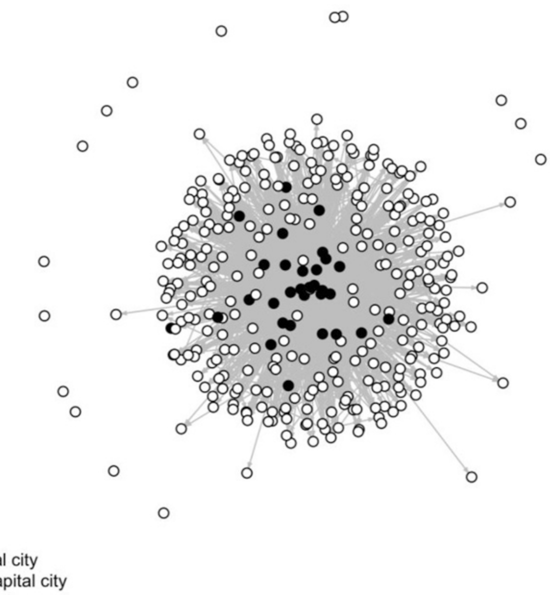
The ERGM approach takes the entire network to analyze the pattern of interactions: ERGM generates all possible networks having n nodes and uses the set of all obtainable random networks to make statistical inferences about how certain model covariates (e.g., whether region i and j belong to the same linguistic origin) are more commonly observed in the realized network than might be expected by a pure chance. ERGM uses the Markov chain Monte Carlo procedure to estimate parameter values for model covariates that maximize the likelihood of the set of observed ties. More information about the ERGM for a valued network is available in Krivitsky (2012) and Krivitsky et al. (2013).

4.2. Teleconsultation Network

For our main ERGM analysis, we construct a teleconsultation network using the entire 10-year data of teleconsultation instances. Because of the technicalities and substantial computational cost, valued ERGM estimates parameters based on a cross-sectional network. To alleviate identification concerns because of this cross-sectional treatment, we conduct multiple robustness checks in Section 6. We also discuss the limitations and implications of this cross-sectional treatment in Section 7.

The teleconsultation data allow us to analyze the pattern of virtual healthcare delivery through teleconsultations. To construct a teleconsultation network, we track the frequency of teleconsultations between regions. Specifically, if a physician in region i offered a teleconsultation to a patient in region j, this instance is captured as a healthcare flow from region i to j. The teleconsultation network is a one-mode network with a size $n \times n$, where n is 336, the number of regions.

Figure 4. Teleconsultation Network

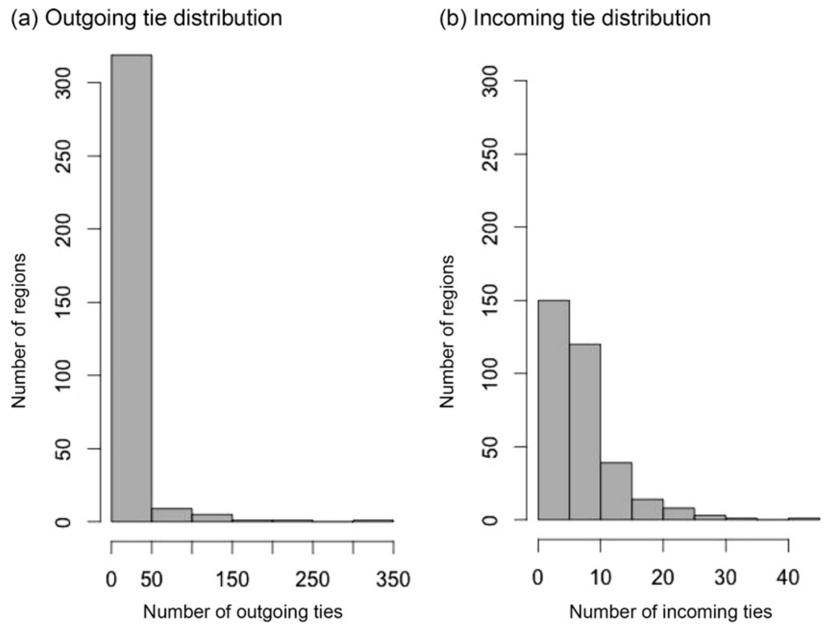


The teleconsultation network is represented in an adjacency matrix $TC = \{a_{ij}\}$, where i and j represent regions. Each cell value a_{ij} represents the frequency of teleconsultations from region i to j, where $a_{ij} = \{0, 1, 2, 3, \ldots\}$. Ties in the teleconsultation network are directional, in that a_{ij} may be different from a_{ji}.

Figure 4 depicts the teleconsultation network during our empirical period. To enhance readability, isolates (i.e., regions with no ties to or from other regions) are excluded. The figure shows that many capital cities are located at the core, indicating that those cities are active in teleconsultations. Specifically, 65.7% of participating physicians are in capital cities, and the remaining 34.3% of physicians are in noncapital regions. This is a highly disproportionate share, given that only 31 out of 336 regions are capital cities. Participating patients are more evenly distributed across regions than physicians: 50.5% (49.5%) of participating patients are in noncapital (capital) regions.

The network density, defined as the probability that any pair of regions has a teleconsultation tie, is 0.022. Distributions of outgoing and incoming ties across regions show an interesting pattern. As depicted in Figure 5(a), the distribution of outgoing ties is highly skewed to the right, indicating that physicians in a few regions provide a disproportionately large share of teleconsultations. For instance, Beijing's outgoing ties are 306, meaning that physicians in Beijing offered teleconsultations to patients in 306 regions. On the contrary, the distribution of incoming ties (participating patients) is less skewed across regions (Figure 5(b)).

Figure 5. Indegree and Outdegree Distribution of Teleconsultation Network



4.3. Network Variables

We incorporate a rich set of network variables to generate a family of graphs for ERGM analysis. In the following subsections, we describe how we constructed our network variables. We normalized all network variables so that their values lie between 0 and 1 for comparability. At the end of this section, we provide a summary of the variables in Table 1.

4.3.1. Offline Health Resource Variables. The first research goal of this study is to examine cross-regional teleconsultation patterns, which illuminate an important social implication on the role of teleconsultations in geographic healthcare disparity. For this goal, we incorporate the following network variables.

First, we include *AbsDiff*(*Offline health resource*). This term captures the expected number of teleconsultations between regions as a function of their absolute difference in offline health resources. The estimate of this variable informs us as to whether teleconsultations tend to connect regions with larger or smaller offline resource gaps. We measure each region's offline health resources in two aspects: medical professional-based and facility-based measures. For a professional-based measure, we employed per capita physician supply. For facility-based measures, we used the per capita number of hospital beds obtained from the 2006–2015 volumes of the *China Statistical Yearbook of Health and Family Planning*. Incorporating both professional- and facility-based measures allows us to gain comprehensive insights into how teleconsultations mobilize offline healthcare. A positive (negative) estimate of the variable would suggest that teleconsultations tend to happen more often between regions with a larger (smaller) offline resource gap.

Although *AbsDiff*(*Offline health resource*) offers valuable insight into whether teleconsultations bridge regions with large resource gaps, it does not inform us of its direction: from where it originates and to where it is directed. To investigate the directionality, we further include the following two variables: *NodeInCov*(*Offline health resource*) and *NodeOutCov*(*Offline health resource*). These two variables capture the expected number of incoming and outgoing tie formations as a function of a region's offline health resources level, respectively. A negative estimate of *NodeInCov*(*Offline health resources*) would suggest that the expected number of incoming ties increases as a region has lower levels of offline health resources, implying that underserved regions are recipients of teleconsultations. Similarly, a positive estimate of *NodeOutCov*(*Offline health resources*) would suggest that the expected number of outgoing ties increases as a region has higher levels of health resources, implying that resourceful regions are providers of teleconsultations.

Finally, we incorporate a variable, *High-to-Low*, to compare the likelihood of teleconsultations from high- to low-resource regions relative to that from low- to high-resource regions. For this analysis, we divided regions into two groups: the High group and Low group. Regions that belong to the High group possess more than the median level of offline health resources, and those that belong to the Low group possess less than the median level. The term

Table 1. Summary of ERGM Network Variables

Article I. Network variable	Article I. Definition
Offline health resource variables	
AbsDiff(*Offline health resource*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their absolute difference in offline health resources
NodeInCov(*Offline health resource*)	A variable capturing the tendency of a region to form more *incoming* teleconsultation ties as a function of its offline health resources
NodeOutCov(*Offline health resource*)	A variable capturing the tendency of a region to form more *outgoing* teleconsultation ties as a function of its offline health resources
High-to-Low	A variable capturing the tendency of a network to form more teleconsultation ties from high- to low-resource regions, relative to low- to high-resource regions
Friction variables	
EdgeCov(*Language barrier*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their difference in linguistic origins
EdgeCov(*Cultural difference*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their difference in cultural origins
EdgeCov(*Limited media coverage*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their limited media coverage
EdgeCov(*Physical distance*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their physical distance
EdgeCov(*Mobility restriction*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of their limited accessibility through public transportations
EdgeCov(*Different jurisdiction*)	A variable capturing the tendency of a region pair to form stronger teleconsultation ties as a function of them not belonging to the same jurisdiction
Other control and network structural variables	
NodeCov(*Population*)	A variable capturing the tendency of a region to form more teleconsultation ties as a function of its population
NodeCov(*Per capita GDP*)	A variable capturing the tendency of a region to form more teleconsultation ties as a function of its per capita GDP
NodeCov(*Internet penetration ratio*)	A variable capturing the tendency of a region to form more teleconsultation ties as a function of its Internet penetration ratio
NodeCov(*Offline insurance restriction*)	A variable capturing the tendency of a region to form more teleconsultation ties as a function of geographic restriction of its residents' offline health insurance
Mutuality	A variable capturing network structural tendency to form a tie $j \rightarrow i$ when a tie $i \rightarrow j$ is present
Triadic closure	A variable capturing network structural tendency to form a tie $j \rightarrow k$ when $i \rightarrow j$ and $i \rightarrow k$ ties are present
Nonzero	A variable that corrects for zero inflation of outcome network
Sum	The intercept term evaluating the sum of the values of all the relations

High-to-Low captures the prevalence of ties from high-resource to low-resource regions, and *Low-to-High* captures those from low-resource to high-resource regions. We set *Low-to-High* as a control group, so the positive estimate of *High-to-Low* indicates that teleconsultations from high-resource to low-resource regions are more common than its base case, *Low-to-High*.

4.3.2. Friction Variables. Our second research goal is to examine social, information, and geography frictions in teleconsultations. To achieve this, we explore several key factors, though it is not feasible to generate an exhaustive set of the factors that create frictions.[4]

First, we incorporate *EdgeCov*(*Language barrier*) and *EdgeCov*(*Cultural difference*) to examine social friction. *EdgeCov*(*Language barrier*) is a dummy variable that takes the value of 1 if a region pair is from different linguistic origin and 0 otherwise, according to the classification of Liu et al. (2015). A negative coefficient of *EdgeCov*(*Language barrier*) implies the presence of friction as a result of differences in dialects. Second, the variable *EdgeCov*(*Cultural difference*) takes a value of 1 if a region pair belongs to different cultural groups according to the classification of Yuan and Chen (2014) and 0 otherwise. Similar to *EdgeCov*(*Language barrier*), a negative coefficient of *EdgeCov*(*Cultural difference*) indicates the presence of friction as a result of cultural differences.

Second, we examine information friction in teleconsultations by including *EdgeCov*(*Limited media coverage*). The numbers of shared TV and radio channels are used as a proxy to measure the degree of common information exposure between regions. To make it consistent with other variables that capture friction to teleconsultations, we reverse-coded common media coverage information between regions to capture the degree of "limited" media coverage for each region pair. The negative estimate of *EdgeCov*(*Limited media coverage*) indicates that as exposure to common media decreases between regions, teleconsultations become less frequent.

Third, we incorporate *EdgeCov*(*Mobility restriction*), *EdgeCov*(*Jurisdiction difference*), and *EdgeCov*(*Physical distance*) to examine geography friction in teleconsultation flows. *EdgeCov*(*Mobility restriction*) tests whether offline accessibility between regions may affect teleconsultation flow. *EdgeCov*(*Mobility restriction*) is coded as 1 if the pair is not connected with a high-speed train system and 0 otherwise. Negative coefficients of *EdgeCov*(*Mobility restriction*) indicate that fewer teleconsultations occur if two regions are not connected with a train system. *EdgeCov*(*Jurisdiction difference*) examines whether the expected number of teleconsultations between regions i and j varies as a function of whether the two regions are within the same jurisdiction border or not. If a region i and j pair is not within the same jurisdiction boundary (i.e., a different province in our context), the pair is coded as 1 and 0 otherwise. The *EdgeCov*(*Jurisdiction difference*) captures the factors that make patients favor physicians inside the patients' jurisdiction boundary over those outside of it. After controlling for linguistic differences, cultural differences, and mobility restrictions, factors such as patients' psychological closeness to within-border physicians may contribute to the effect of *EdgeCov*(*Jurisdiction difference*) on teleconsultation patterns. A negative estimate indicates that a smaller number of teleconsultations tend to occur if regions do not belong to the same jurisdiction.

Last, we incorporate *EdgeCov*(*Physical distance*) to make an inference about whether distance friction exists. We construct this variable by calculating the shortest distance between region i and j based on their longitudinal and latitudinal data. If distance friction exists, the estimate of *EdgeCov*(*Physical distance*) would be negative, indicating that a smaller number of teleconsultations occur as region i and j become more distant.

4.3.3. Control Variables. We also incorporate several variables to control for other factors that may influence teleconsultation flows between regions. First, regions with a larger population are more likely to form a greater number of teleconsultation ties because of their pure size effect. To control for this effect, we incorporate *NodeCov*(*Population*) based on each region's total population as recorded in the 2006–2015 volumes of the *China Statistical Yearbook*. A positive estimate indicates that regions with a larger population tend to form greater teleconsultation ties.

Second, patients and physicians residing in wealthier regions are expected to be more educated, tech-savvy, and more aware of teleconsultation services. To control for this economic wealth effect, we construct *NodeCov*(*Per capita GDP*) by dividing each region's GDP by its total population, with data obtained from the 2006–2015 volumes of the *China Statistical Yearbook*. A positive estimate indicates that regions with higher per capita GDP tend to form a greater number of teleconsultation ties.

Third, patients and physicians in regions with better access to the internet are more likely to participate in teleconsultations. We include *NodeCov*(*Internet penetration ratio*) to control for such an effect. The internet penetration ratio not only captures each region's capability of using the teleconsultation service but also captures regional variations in information exposure through the internet channel (e.g., websites, social media). A positive estimate indicates that regions with higher internet penetration ratios tend to form a greater number of teleconsultation ties.

Fourth, although health insurance provides nationwide coverage for all residents in China, the insurance enforces unfavorable insurance reimbursement rates for some rural patients when they meet nonlocal physicians. To control for the effect driven by offline insurance restriction, we include *NodeCov*(*Offline insurance restriction*).

In addition, we include several network structural covariates to control for structural processes that may affect the likelihood of teleconsultation tie formation. The term *Mutuality* captures the tendency of network ties to be reciprocated. That is, mutuality indicates that if a tie from node i to j exists ($i \rightarrow j$), it significantly increases the likelihood of tie formation from node j to i ($j \rightarrow i$). A positive estimate suggests the presence of reciprocity. The term *Triad closure* measures the tendency of the closure of triads. A positive estimate of *Triadic closure* suggests that when ties of $i \rightarrow j$ and $i \rightarrow k$ exist, these existing ties increase the likelihood of tie formation between j and k. We added the term *Nonzero* to correct for zero inflation of the teleconsultation network. Zero inflation refers to the phenomenon that valued networks are often sparse, but if two nodes do interact, their interaction count is relatively high. Finally, different regions may have different overall propensities to interact. To capture such individual heterogeneity, we include the term *Nodesqrtcovar*. This term adds a measure of covariance among all region pairs that include the same region.

5. Results

5.1. The Role of Teleconsultations in Offline Resource Disparity

In this section, we present the results of ERGM analyses examining whether teleconsultations generate a virtual flow of healthcare to alleviate offline resource disparity.

5.1.1. Teleconsultations Across Resourceful and Underserved Regions. Table 2 presents the results of our ERGM analyses. Model 1 includes only control and network structural variables. To look into how teleconsultations connect resource-rich and resource-poor regions, we introduce a set of network variables capturing offline health resources in Models 2–7. In these analyses, we use two aspects to capture offline health resources: one based on medical professionals (i.e., per capita physician counts) and the other based on medical facilities (i.e., per capita hospital beds). Models 2–4 report results based on medical professionals, and Models 5–7 present results based on medical facilities. The direction and statistical significance of estimates are consistent across the two measures of offline health resources.

In Models 2 and 5, we incorporate the *AbsDiff*(*Offline health resource*) term to examine how the degree of the offline health resource gap between two regions affects their teleconsultation frequencies. The estimate of *AbsDiff*(*Offline health resource*) is positive and significant in both models, suggesting that teleconsultation frequency increases as two regions' offline health resource gap increases, holding other factors constant. This is an exciting finding, as it shows that teleconsultations can be a bridge between regions with a big resource gap.

Table 2. ERGM Results: Teleconsultations Across Resourceful and Underserved Regions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Offline health resource measure		Medical professionals			Medical facilities		
Offline Health resource disparity							
AbsDiff(*Offline health resource*)		1.12***			0.78***		
		(0.06)			(0.03)		
NodeInCov(*Offline health resource*)			−0.45***			−0.24***	
			(0.11)			(0.05)	
NodeOutCov(*Offline health resource*)			4.43***			2.12***	
			(0.09)			(0.03)	
High-to-Low				0.92***			0.80***
				(0.06)			(0.06)
Control and network structural variables							
NodeCov(*Population*)	1.27***	1.28***	1.56***	1.58***	1.32***	1.45***	1.60***
	(0.05)	(0.06)	(0.05)	(0.08)	(0.08)	(0.06)	(0.09)
NodeCov(*Per capita GDP*)	0.53***	0.32***	0.31***	0.42***	0.36***	0.32***	0.43***
	(0.03)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)
NodeCov(*Internet penetration*)	0.72***	0.57***	0.97***	1.01***	0.67***	0.87***	1.03***
	(0.06)	(0.08)	(0.09)	(0.10)	(0.08)	(0.09)	(0.10)
NodeCov(*Offline insurance restriction*)	−0.89***	−0.91***	−0.31***	−0.69***	−0.95***	−0.26***	−0.71***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)
Sum	0.98***	0.99***	0.98***	0.99***	0.86***	0.88***	0.86***
	(0.09)	(0.12)	(0.11)	(0.11)	(0.10)	(0.09)	(0.10)
Nonzero	−6.47***	−6.28***	−5.87***	−5.95***	−5.67***	−5.12***	−5.75***
	(0.06)	(0.07)	(0.06)	(0.06)	(0.04)	(0.04)	(0.06)
Mutuality	0.55***	0.39***	0.46***	0.43***	0.40***	0.43***	0.41***
	(0.04)	(0.03)	(0.05)	(0.06)	(0.03)	(0.04)	(0.06)
Triadic closure	0.11	0.12	0.11	0.10	0.09	0.10	0.10
	(0.12)	(0.14)	(0.10)	(0.09)	(0.14)	(0.10)	(0.09)
Nodesqrtcov	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Number of nodes = 336 (regions). The dependent variable is teleconsultation frequencies from region i to j. In Models 4 and 7, the control group is *Low-to-High*. Individual heterogeneity is captured by *Nodesqrtcovar*; heterogeneity of teleconsultation flows by medical specialties is controlled by *NodeFactor*(*Medical specialties*). The term *Nonzero* corrects for zero inflation of the teleconsultation network. For comparability, all network variables are scaled to values between 0 and 1.

***$p < 0.001$.

Although the *AbsDiff*(*Offline health resource*) term informs us that teleconsultations are more frequent between regions with a larger offline resource gap, it does not inform us of the direction of teleconsultations. To investigate its directionality, we incorporate *NodeInCov*(*Offline health resource*) and *NodeOutCov*(*Offline health resource*) terms in Models 3 and 6. The negative estimate of *NodeInCov*(*Offline health resource*) indicates that abundant regions tend to form fewer incoming teleconsultation ties. That is, patients in resource-rich (resource-poor) regions tend to get fewer (more) teleconsultations. By contrast, the positive estimate of *NodeOutCov*(*Offline health resource*) indicates that the propensity of forming outgoing teleconsultation ties increases as a region's offline resource increases. Put differently, physicians in resource-rich (resource-poor) regions tend to provide more (less) teleconsultations. Taken together, the results of *NodeInCov*(*Offline health resource*) and *NodeOutCov*(*Offline health resource*) suggest that teleconsultations originate from resourceful regions and are directed toward underserved regions—the desirable direction that can alleviate offline health resource disparity.

Finally, we incorporate the network variable *High-to-Low* in Models 4 and 7. This variable allows us to compare the likelihood of teleconsultation ties from high- to low-resource regions relative to that from low- to high-resource regions. The estimate of *High-to-Low* is positive and statistically significant, suggesting that teleconsultations from high- to low-resource regions are more likely to form than those from low-to high-resource regions. In sum, the results of a set of variables—*AbsDiff*(*Offline health resource*), *NodeInCov*(*Offline health resource*), *NodeOutCov*(*Offline health resource*), and *High-to-Low*—provide encouraging evidence that teleconsultations mobilize healthcare in a direction that could mitigate resource disparity.

Across all the models, we incorporated several network structural variables to control the self-organizing properties of networks. The term *Sum* is an intercept capturing the baseline probability of network ties. The term *Nonzero* corrects for zero inflation of the teleconsultation network, and its negative estimate suggests the presence of zero inflation in the teleconsultation network. The positive estimate of *Mutuality* indicates that if a teleconsultation tie from region i to j exists, ties from j to i are more likely. The estimate of the *Triadic closure* term is not statistically significant, indicating that the presence of ties from i to j and i to k does not increase the likelihood of a tie between j and k. The term *Nodesqrtcovar* controls individual region heterogeneity.

In addition, we incorporate *NodeCov*(*Population*), *NodeCov*(*Per capita GDP*), *NodeCov*(*Internet penetration*), and *NodeCov*(*Offline insurance restriction*) to control for the effects from each region's population size, economic wealth, internet penetration ratio, and offline health insurance restriction on their teleconsultation frequencies. Not surprisingly, wealthier regions with large populations engage more in teleconsultations. Furthermore, a region's internet penetration ratio increases its engagement level with teleconsultations, but offline insurance restriction lowers engagement with teleconsultations.

5.1.2. Teleconsultations Across Urban and Rural Areas. As a supplement to the analyses in Section 5.1.1, we analyze how teleconsultations mobilize healthcare across urban and rural areas. The results are presented in Table 3. For this analysis, we collected information about the urbanization level of each region, which is based on several factors such as GDP, population density, and infrastructure (Sina News 2017). The urbanization levels vary from 1 to 5, where the least urbanized regions belong to level 1 and the most urbanized regions belong to level 5. The degree distribution of urban and rural areas offers descriptive insight into how urban and rural areas utilize teleconsultations. Urbanized regions (those belong to levels 4 and 5) have higher outdegree centrality than do rural regions (those belong to levels 1, 2, and 3),[5] indicating that urban areas are providers and rural areas are recipients of teleconsultations.

We use two network variables, *NodeInFactor* (*Urbanization level*) and *NodeOutFactor* (*Urbanization level*), to analyze teleconsultation flow across urban and rural regions. *NodeInFactor* (*Urbanization level*) estimates how urbanization influences the likelihood of forming *incoming* teleconsultation ties. Similarly, *NodeOutFactor* (*Urbanization level*) estimates the impact of urbanization on the likelihood of forming *outgoing* teleconsultation ties. The least urbanized regions (level 1) are used as the control group. Consistent with the previous results that resource-poor regions are the recipients of teleconsultations, we find that rural regions tend to be the recipients of teleconsultations. The results indicate that the estimates of *NodeInFactor* (*Urbanization level*) of urbanization levels 2–5 regions are negative and significant. Because the control group is the most rural group, the negative estimates of *NodeInFactor* (*Urbanization level*) indicate that as regions become more urbanized, they receive a smaller number of teleconsultations than the most rural region (i.e., patients in more urbanized regions get fewer teleconsultations from other regions). On the other hand, the estimates of *NodeOutFactor* (*Urbanization level*) are positive and significant, indicating that more urbanized regions tend to be providers of teleconsultations.

5.2. Frictions to Teleconsultation Flows

5.2.1. Effects of Social, Information, and Geography Friction on Teleconsultation Flow. Teleconsultations are meant to facilitate the free flow of healthcare across

Table 3. ERGM Results: Teleconsultations Across Urban and Rural Regions

Health resource variable	Medical professionals	Medical facilities
NodeInFactor(*Urbanization level: 2*)	−0.40***	−0.26***
	(0.05)	(0.03)
NodeInFactor(*Urbanization level: 3*)	−0.44***	−0.34***
	(0.04)	(0.01)
NodeInFactor(*Urbanization level: 4*)	−0.82***	−0.49***
	(0.06)	(0.04)
NodeInFactor(*Urbanization level: 5*)	−1.38***	−0.81***
	(0.06)	(0.06)
NodeOutFactor(*Urbanization level: 2*)	2.18***	0.96***
	(0.38)	(0.11)
NodeOutFactor(*Urbanization level: 3*)	3.35***	2.21***
	(0.36)	(0.14)
NodeOutFactor(*Urbanization level: 4*)	4.39***	2.78***
	(0.36)	(0.19)
NodeOutFactor(*Urbanization level: 5*)	5.33***	3.90***
	(0.35)	(0.18)
All control and network structural variables	Yes	Yes

Notes. Number of nodes = 336 (regions). The dependent variables is teleconsultation frequencies from region *i* to *j*. The urbanization levels vary from 1 to 5, where the least urbanized regions belong to level 1, and the most urbanized regions belong to level 5; the control group is urbanization level 1 regions (the least urbanized regions).
***$p < 0.001$.

regions, yet, as we discussed in Section 2, several factors may hinder cross-regional teleconsultations. The focus of this section is to understand the sources of such friction.

Across all the models in Table 4, we included *AbsDiff*(*Offline health Resource*) to control for the effect of offline resource disparity on teleconsultation frequencies. In addition, we included all network structural and control variables that we incorporated in Table 2. We introduce friction variables across columns to demonstrate the stability of the results. Models 1 and 2 incorporate two variables, *EdgeCov*(*Language barrier*) and *EdgeCov*(*Cultural difference*) to examine social friction. Model 3 incorporates *EdgeCov*(*Limited media coverage*) to examine information friction. Models 4, 5, and 6 incorporate three variables—*Edgecov*(*Physical distance*),

Table 4. ERGM Results: Frictions to Teleconsultations

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Health resource variables							
AbsDiff(*Health resource*)	1.19***	1.59***	1.24***	1.24***	1.58***	1.56***	1.88***
	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)
Friction variables							
Social friction							
EdgeCov(*Language barrier*)	−0.27***						−0.14**
	(0.02)						(0.04)
EdgeCov(*Cultural difference*)		−0.23***					−0.14**
		(0.03)					(0.04)
Information friction							
EdgeCov(*Limited media coverage*)			−0.18***				−0.13***
			(0.02)				(0.03)
Geography friction							
EdgeCov(*Physical distance*)				−4.10***			−2.69***
				(0.14)			(0.13)
EdgeCov(*Different jurisdiction*)					−0.12***		−0.08***
					(0.03)		(0.01)
EdgeCov(*Mobility restriction*)						−0.18***	−0.11***
						0.01)	(0.00)
All control and network structural variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Number of nodes = 336 (regions). The dependent variable is teleconsultation frequencies from region *i* to *j*.
***$p < 0.001$; **$p < 0.01$.

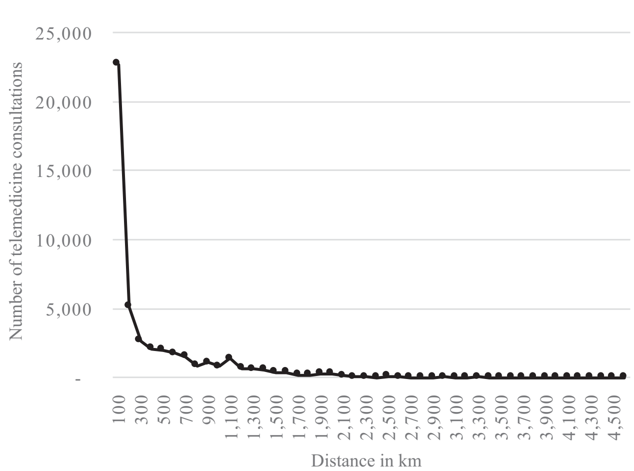
EdgeCov(*Jurisdiction difference*), and *EdgeCov*(*Mobility restriction*)—to examine geography frictions. Finally, we incorporate all friction variables simultaneously in Model 7. Because the direction and the significance of coefficients are stable across all models, we use the complete specification (Model 7) to discuss our results.

The results suggest that social, information, and geography frictions hamper teleconsultation flows. The parameter estimates for both social friction variables, *EdgeCov*(*Language barrier*) and *EdgeCov*(*Cultural difference*), are negative and statistically significant, indicating that teleconsultations are less likely if regions do not have common dialects and culture. The negative effect of *EdgeCov*(*Language barrier*) is a bit surprising, because patients and physicians should be able to communicate using the official standard language. The negative and statistically significant estimate of *EdgeCov*(*Limited media coverage*) indicates that information friction interferes with teleconsultation flows: teleconsultations become less frequent as region pairs share less common media coverage. This result suggests that even though patients can theoretically reach out to any participating physicians in the platform, they usually limit their consideration set to those they may have heard of through offline media exposure.

Finally, we tested whether geography friction exists in teleconsultation flow. Preliminary analysis shows that distance friction, indeed, exists in teleconsultations. Figure 6 illustrates the frequency of teleconsultations across the varying distances between regions *i* and *j*. From the graph, we can observe a significant drop in the number of teleconsultations as the distance between the two regions increases. The negative and statistically significant estimate of *Edgecov*(*Physical distance*) confirms the presence of distance friction; that is, teleconsultation frequency decreases as two regions become farther apart.

We also observe a border effect in teleconsultation flow: the estimate of *EdgeCov*(*Jurisdiction difference*) is

Figure 6. Distance Friction of Teleconsultation Flows



negative and statistically significant, meaning that fewer teleconsultations tend to happen across regions in different provinces, holding other factors—including distance—constant. We further incorporate *EdgeCov*(*Mobility restriction*) to estimate the effect of physical accessibility between regions on their teleconsultation frequencies. In this analysis, we used high-speed train availability data to capture regions' accessibility through public transportation. The negative and significant estimate for *EdgeCov*(*Mobility restriction*) indicates that teleconsultations become less frequent if regions are less accessible through high-speed trains, again after holding other factors such as distance constant. This result is interesting, as it suggests that public transportation accessibility is an important factor in choosing physicians for teleconsultations. In Section 6, we check the robustness of this result by utilizing domestic flight availability data as an alternative measure of mobility restriction between regions. The results are consistent. In the following subsections, we examine two potential mechanisms that may contribute to the observed geography friction.

5.2.2. Low Bandwidth of a Teleconsultation Channel.

As one plausible mechanism of why long-distance teleconsultations might be less likely, we proposed the low information bandwidth of a teleconsultation channel. Because teleconsultations have low bandwidth (i.e., limited capability to support touch-and-feel interactions), patients may prefer nearby physicians, anticipating follow-up office visits or laboratory tests. If this were the case, we would observe that patients with illnesses requiring rich information gathering exhibit stronger preference toward nearby physicians than do patients needing less touch-and-feel interactions.

To examine the low bandwidth mechanism, we first classified illnesses based on how much touch-and-feel interactions they require for treatment. From our interviews with physicians, we learned that illnesses that involve surgical operations as a treatment option require a greater degree of touch-and-feel information gathering than illnesses that do not. Hence, we carefully classified all of our 119,820 teleconsultation instances into surgical and nonsurgical instances based on the specialty categorization of the American Board of Medical Specialties.[6] The American Board of Medical Specialties categorizes medical specialties into surgical and nonsurgical specialties based on whether treatments of illnesses generally require surgeries. Examples of surgical specialties are orthopedic surgery and cardiac surgery, which usually employ operations to treat an illness or injury by cutting, abrading, suturing, or otherwise physically changing body tissues and organs. On the other hand, mental illnesses do not require surgical procedures (e.g., depression); consequently, the necessity

Table 5. Impact of Frictions: Surgical vs. Nonsurgical Teleconsultations

Model	Surgical specialties	Nonsurgical specialties
Social friction		
EdgeCov(*Language barrier*)	−0.15**	−0.11**
	(0.04)	(0.03)
EdgeCov(*Cultural difference*)	−0.14**	−0.11**
	(0.04)	(0.03)
Information friction		
EdgeCov(*Limited media coverage*)	−0.15***	−0.12***
	(0.03)	(0.02)
Geography friction		
EdgeCov(*Physical distance*)	−3.45***	−1.12**
	(0.21)	(0.13)
EdgeCov(*Different jurisdiction*)	−0.10***	−0.06**
	(0.01)	(0.02)
EdgeCov(*Mobility restriction*)	−0.18***	−0.05***
	(0.00)	(0.00)
Health resource variable	Yes	Yes
All control and network structural variables	Yes	Yes

Notes. Number of nodes = 336 (regions). The dependent variable is teleconsultation frequencies from region i to j.
***$p < 0.001$; **$p < 0.01$.

for precise physical examination through touch-and-feel interaction is relatively less.

After classifying teleconsultations, we ran ERGM for surgical and nonsurgical teleconsultations separately. If the low bandwidth mechanism were at play, we would expect the constraining effects of geography frictions to be stronger for surgical teleconsultations than for nonsurgical teleconsultations. The results are presented in Table 5. Consistent with our expectation, we find that the effects of geography frictions are more pronounced for surgical illnesses than for nonsurgical illnesses.

5.2.3. Financial Constraint of Patients in Underserved Regions.

As another plausible mechanism, we proposed that rural patients may not seek long-distance care because they cannot afford the consultation fees of high-quality physicians in distant regions. To empirically test this possibility, we compared the coefficients of *EdgeCov*(*Physical distance*) across rural patients' consultations of different price ranges: (1) price higher than the median price ($11 per 10 minutes) versus (2) price lower than or equal to the median price. For convenience, we call the former "expensive" consultations and the latter "inexpensive" consultations. The result of this analysis is presented in Table 6. Consistent with our conjecture, we find that the negative impact of physical distance is stronger for expensive consultations than for inexpensive consultations. The impact of physical distance on inexpensive teleconsultations is almost negligible ($\theta = -0.32$, $p < 0.001$), whereas expensive teleconsultations are much more constrained by distance ($\theta = -2.59$, $p < 0.001$). This result is alarming because it indicates that rural regions are again lacking access to complicated and expensive procedures—presumably, specialty care—which need the most significant boost through telehealth.

To provide corroborating evidence, we also analyzed whether teleconsultations by chief physicians—the highest-ranked physicians who charge the highest fees (on average, $30 for 10 minutes with a maximum of $155 for 10 minutes)—are more limited by distance than are consultations by lower-ranked physicians. Similar to the previous analysis, we constructed two

Table 6. Impact of Physical Distance: Expensive vs. Inexpensive Teleconsultations

Model	Expensive	Inexpensive
EdgeCov(*Physical distance*)	−2.59***	−0.32***
	(0.09)	(0.00)
Health resource variable	Yes	Yes
All other friction variables	Yes	Yes
All control and network structural variables	Yes	Yes

Notes. The dependent variable is teleconsultation frequencies from region i to j. This analysis only considered teleconsultations of rural patients who reside in regions with urbanization levels 1 and 2.
***$p < 0.001$.

Table 7. Impact of Physical Distance: Chief Physician vs. Lower-Ranked Physician Teleconsultations

Model	Chief physician	Lower-ranked physician
EdgeCov(*Physical distance*)	−3.78***	−0.47***
	(0.28)	(0.01)
Health resource variable	Yes	Yes
All other friction variables	Yes	Yes
All control and network structural variables	Yes	Yes

Notes. Number of nodes = 336 (regions). The dependent variable is teleconsultation frequencies from region *i* to *j*.
***$p < 0.001$.

data sets: one capturing only teleconsultations by chief physicians and the other capturing those by lower-ranked physicians. Then, we ran ERGM separately for the two groups. The results of these analyses are presented in Table 7. We found that consultations by chief physicians are more limited by distance than are those of other physicians. This result suggests that lower-ranked physicians are better than high-ranked physicians in reaching out to patients in distant regions.

6. Robustness Checks and Supplementary Analyses

6.1. Results Without Beijing and Shanghai Physicians

We find that physicians in a few regions provide a disproportionately large number of teleconsultations. In particular, physicians in Beijing and Shanghai have provided about 60% of all teleconsultations during our empirical period. To check whether our results are purely driven by the Beijing and Shanghai physicians, we replicate our analysis after excluding all teleconsultations offered by Beijing and Shanghai physicians. After the exclusion, the statistical significance and directions of our results stay consistent with our main results. Table B in the online appendix presents the results of this analysis.

6.2. ERGM Using Lagged Network Variables and Temporal ERGM

Because of the technicalities and substantial computational cost, valued ERGM estimates coefficients based on a cross-sectional network. The main weakness of a cross-sectional model is the potential reverse causality. To alleviate this concern, we run the analysis for each year using lagged data at year $t - 1$. We find that the direction and significance of the results are consistent across time, indicating that reverse causality is unlikely. Table C in the online appendix reports the results of this analysis.

We notice that the coefficient of *AbsDiff*(*Offline health resource*) increases over time. These temporal dynamics suggest that, over time, the teleconsultation service occurs more frequently between two regions that have a larger health resource gap. In other words, teleconsultations play an increasingly bigger role in reducing health resource disparity over time. We suspect that this result is driven by lagged adoption by rural patients. We observe from our data that early adopters of teleconsultation services are mostly urban patients and that rural patients joined later. This observation is consistent with previous studies' findings that rural areas tend to have more barriers to innovative healthcare services than do urban areas. In teleconsultation services, such barriers could be a low awareness of the service and technical knowledge (Helitzer et al. 2003). In addition, we observe that the size of coefficients for most friction variables increases over time. That is, fewer teleconsultations occur if two regions use different dialects or have different cultural origins. Also, we observe that fewer teleconsultations happen if regions are not connected with the high-speed train system. This trend suggests that teleconsultation usage is becoming more constrained by social, information, and geography frictions.

Another concern of cross-sectional analysis is its inability to leverage within region-pair variances across time. To check whether our results stay consistent after incorporating these variances, we conduct panel estimation by using temporal ERGM (TERGM). TERGM is an extension of ERGM designed to accommodate intertemporal dependence in longitudinally observed networks. The extension is accomplished by incorporating network statistics into ERGM specifications that reflect the ways in which previous realizations of the network determine current features of the network (Krivitsky and Handcock 2014).[7] The results of TERGM are presented in Table D in the online appendix. We find that the qualitative interpretation stays unchanged, as the direction and significance of the TERGM results are consistent with those of our main ERGM analysis using valued networks. However, TERGM allows only binary relationships (i.e., whether a tie is present or not), so the magnitudes of effects are not directly comparable.

6.3. Alternative Measure of Mobility Restriction

In our main analysis to investigate distance friction, we used high-speed train availability data to estimate how the degree of mobility restriction between regions affects teleconsultation frequencies. We check the robustness of this result by employing an alternative measure of mobility. Specifically, we collected domestic flight availability data and calculated mobility restriction measures for every region pair in our data set. Overall, we find that regions are much better connected through high-speed trains than are domestic flights. As of 2015, of 112,560 region pairs, only 0.78% had domestic flight routes, whereas 10.42% of region pairs were connected through high-speed trains. Although the estimate of *EdgeCov*(*Mobility restriction*) for domestic flights is less pronounced ($\theta = -0.05$, $p < 0.001$) than that for high-speed trains ($\theta = -0.18$, $p < 0.001$), they are qualitatively consistent, as the direction and the statistical significance stay the same.

6.4. Multicollinearity Check

In general, ERGM can tolerate correlated predictor variables better than generalized linear models (GLMs). A concerning level of multicollinearity in ERGM generally leads to model nonconvergence, so highly collinear models do not yield problematic estimates because they fail to yield estimates. To check whether our model has a multicollinearity issue, we calculated the variance inflation factors (VIFs) of our model variables. In ERGM, we can calculate the shared variance between parameters using a distribution of networks simulated from the parameter estimates of ERGM. The largest VIF of our model variables is 3.88 for *EdgeCov*(*Different jurisdictions*), and the mean VIF of all variables is 1.89. This level of VIFs is low by ERGM standards (and even by GLM standards) (Duxbury 2021), which suggests that multicollinearity is not an issue in our model.

6.5. Alternative Model

We ran a panel regression model to check the robustness of our results. For this regression, we consider all potential ties among the regions to examine how our independent variables affect the strength of teleconsultation ties between regions. Because our outcome variable, teleconsultation frequencies from region i to j, is a count variable, we used a zero-inflated negative binomial regression model. Because a regression model cannot incorporate endogenous tie formation processes (see Section 4.1), network structural terms are not incorporated into this regression analysis. The results of this robustness check are reported in Table E of the online appendix. We find that the direction and significance of all covariates are consistent across our ERGM and the regression model. Consistent with prior work (Kim et al. 2016), we found that the estimates are slightly smaller in ERGM results because ERGM additionally controls for network structural terms.

6.6. Effects of Friction on Rural Regions with Different Population Age

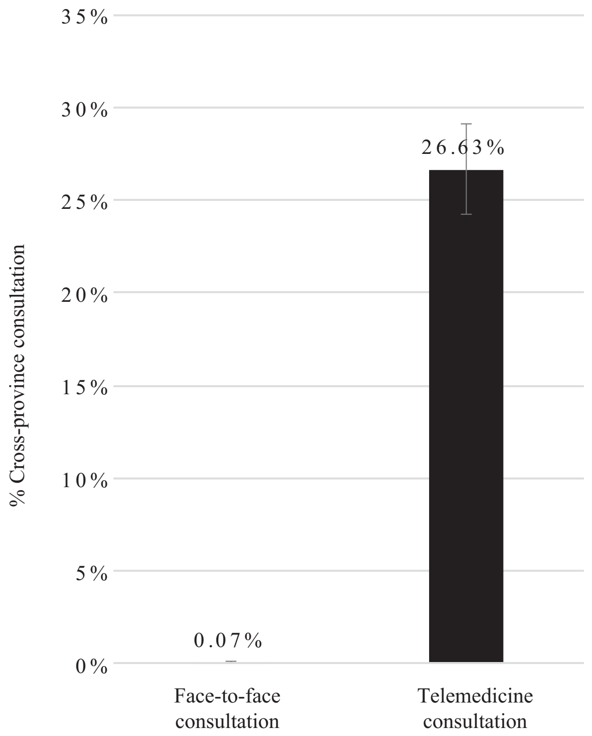
As a supplementary analysis, we checked whether rural regions with a relatively younger population are less affected by frictions than those with the older population. For this analysis, we split the rural regions (the least urbanized regions that belong to urbanization level 1) into two groups based on their percentage of the population over 64 years old. The younger group comprises the rural regions with lower than the median level of the population over 64, and the older group comprises the rural regions with higher than the median level. The median percentage of the population over 64 for the rural regions is 9.48%. We call the younger group *Rural_young* and the older group *Rural_old* for ease of reference. Then, we ran ERGMs separately for the two groups. To minimize confounding effects from the different types of illnesses younger and older populations seek treatment for, we considered only surgical illnesses to compare the two populations' teleconsultation patterns. The results indicate that the *Rural_young* group suffers less from social, information, and geography frictions than does the *Rural_old* group, although the discrepancy is relatively small. The results of this analysis are presented in Table F in the online appendix.

6.7. Comparison with Offline Patient Flow

Our results demonstrate that teleconsultations promote consultations between urban physicians and rural patients who are nearby. Although exciting, this pattern might happen even without teleconsultations. That is, rural patients might travel to nearby urban cities to receive medical consultations. This section looks into whether teleconsultations mobilize healthcare more than patients' offline travel.

To compare offline patient and teleconsultation flow across regions, we collected additional data[8] that contain the proportion of offline medical consultations crossing jurisdiction (province, in our empirical context) borders. We obtained this data set from the Chinese government, the Ministry of Human Resources and Social Security of the People's Republic of China. Taking Guangdong Province as an example, the data set contains the total number of patients who received offline medical consultations in Guangdong Province and how many of them live outside of Guangdong Province. We obtained this statistic for all provinces in China as of 2014. We utilize these data as a benchmark to gauge whether teleconsultation flow is more or less constrained by distance compared with offline

Figure 7. Face-to-Face vs. Telemedicine Consultations: Cross-Province Consultation Ratio



consultations. Figure 7 presents the proportion of cross-province patients for offline and teleconsultations. It shows that this proportion is about 358 times higher in the teleconsultation setting than in the offline setting, and this difference is statistically significant ($t = -10.95$, $p < 0.01$). This large discrepancy of the cross-province consultation ratio suggests that, although still not completely geography-free, teleconsultations mobilize healthcare much farther than patients' travel does.

We further obtained cross-region patient data from a major hospital in Beijing to supplement the aforementioned province-level analysis. This hospital's grade is 3A in the Chinese hospital classification system, indicating that it is one of the highest-quality hospitals responsible for providing medical specialist services and medical education and serving as a medical hub to multiple regions. The hospital provided us with internal data that contain the percentages of their patients coming from different regions for five years (2010–2014). We match these data with our teleconsultation data to compare the same hospital's cross-region patient flow in offline versus teleconsultation settings. Figure 8 illustrates that the ratio of cross-region patients is about four times higher in teleconsultations than in offline consultations, and this difference is statistically significant ($t = 13.09$, $p < 0.001$). Although this comparison is based on one hospital as a result of data limitations, it serves as a useful benchmark. Because high-quality medical resources are concentrated in Beijing, it is well known that many outside patients travel to Beijing to get needed medical care (*China Daily* 2014). As such, major hospitals in Beijing are likely to exhibit higher cross-region patient ratios than average hospitals in other regions. Given that the hospital is one of the highest-quality hospitals in Beijing, its cross-region patient ratio is likely to be higher than that of average hospitals. Consequently, this analysis provides a conservative estimate.

The results from the preceding two analyses suggest that teleconsultations, although still constrained by distance, deliver healthcare above and beyond what has been achieved through patients' travel in the offline setting.

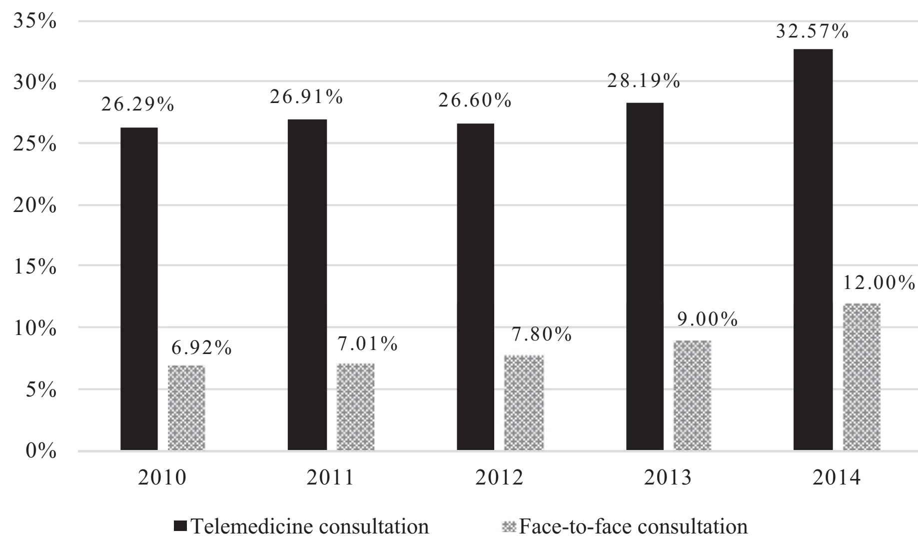
7. Discussions and Conclusion

Many countries are aware of the geographic imbalance in their medical professionals: there are many in urban cities but too few in rural areas. To reduce geographic healthcare disparity, governments have made significant efforts to relocate medical professionals to rural areas, but to little avail. Teleconsultation has emerged as a promising solution to overcome this challenge because it enables long-distance diagnosis and treatment. In fact, many government agencies have already been investing in telemedicine initiatives. For example, in a move to increase rural residents' access to healthcare, the United States Department of Agriculture invests $42 million in telehealth infrastructure (Siwicki 2021). The private sector has followed suit; for example, during the first quarter of 2016, the private sector in the United States invested $171 million in the telemedicine industry (Sullivan 2016). Investors see telemedicine platforms as a market poised for explosive growth.

To advance our understanding of teleconsultations' potential in redistributing healthcare, we compiled a unique data set that combines teleconsulting activities, offline healthcare resources, and regional characteristics. Our empirical analysis presents encouraging evidence that teleconsultations can promote medical consultations between physicians in resourceful areas and patients in underserved areas. Nonetheless, we also found that such delivery is constrained by social, information, and geography frictions.

Our study makes several contributions to the previous literature. To begin with, this study contributes to the telemedicine literature. Previous studies focused mostly on telehealth technology (e.g., Elion and Petrocelli 1994, Hostetler 1994, and Perednia and Allen 1995), determinants of physicians' adoption decisions (e.g., Hu et al. 1999 and Wang et al. 2020), and the economic feasibility of telemedicine (e.g., Dávalos et al. 2009, Polisena et al. 2009, and Rajan et al. 2019). With the growing adoption of telemedicine, recent studies

Figure 8. Face-to-Face vs. Teleconsultations: Cross-Region Consultation Ratio of a Beijing 3A Hospital



have examined the implications of telehealth interventions on patients' health outcomes (Thomas et al. 2009, Buck and Almis 2017, Dang et al. 2017, Bavafa et al. 2018) and hospital operations (Sun et al. 2020).

Our study joins the scant medical literature that studies the potential of telemedicine services in reducing offline healthcare disparities. Marcin et al. (2016) theoretically discussed telemedicine's potential to address pediatric health disparities in rural communities, and deShazo and Parker (2017) provided a case study on how the state of Mississippi was able to deploy telemedicine to rural areas with limited resources despite conflict among stakeholders. Although these studies provide valuable insights about how to deploy telemedicine technologies, surprisingly little attention has been paid to systematic empirical investigation of how physicians and patients are actually utilizing the deployed telemedicine service. Telemedicine technology makes additional healthcare options available, but the true impact of the technology depends on how patients actually use it (Zammuto et al. 2007). This study advances our understanding of this matter by empirically analyzing a large-scale data set covering one entire country, diverse illnesses, heterogeneous patient groups, and a longer time frame (10 years).

Moreover, this study contributes to the information systems literature studying the societal impact of information technology (IT). Prior studies offer valuable insights on the societal impact of IT in various contexts such as racial hate crime (Chan et al. 2016), sex crime (Chan et al. 2019), homicide (Greenwood and Wattal 2017), bankruptcy (Burtch and Chan 2019), civilian safety (Pang and Pavlou 2019), road congestion (Cheng et al. 2020), and HIV transmission (Chan and Ghose 2014). Our study contributes to this line of research by examining whether and how teleconsultations (IT-enabled healthcare) mobilize healthcare resources to reduce healthcare disparities. Because the geographic imbalance of healthcare is a long-standing, notorious social problem, it is surprising how little attention has been paid to the ways that IT may improve this challenge, except for the recent study by Goh et al. (2016), who studied patient-to-patient social and emotional support messages in an online health community and found that rural patients tend to be net recipients of peer support. As an implication of their finding, the authors state that additional peer support is expected to improve rural patients' health capabilities, which in the long run may reduce geographic health disparity.

Our study adds additional value to the findings of Goh et al. (2016) in several ways. First of all, the research contexts are fairly different. Our setting is a telemedicine platform where physicians offer real medical care in exchange for a fee. By contrast, the context of Goh et al. (2016) is an online platform for exchanging patient-to-patient emotional/social support. This context difference creates several fundamental distinctions between the two studies. That is, although Goh et al. (2016) offer valuable insight into how online peer support may improve the health capabilities of rural patients, they do not inform us how actual medical service may be virtually mobilized to reduce offline healthcare disparities. By analyzing offline health resource distribution and virtual medical care flows over 10 years, our study offers an insight into how IT-enabled healthcare may balance healthcare access across geography.

Besides, different from Goh et al. (2016), our study investigates frictions of virtual healthcare flow. Although teleconsultations are "virtual," which is supposedly geography-free, we find that they are hampered by several factors. Our study uncovers social, information, and geography factors that suppress teleconsultations. Identifying obstacles of teleconsultations can help healthcare providers and policy makers generate strategies to boost teleconsultations. Additionally, whereas Goh et al. (2016) limited their analysis to a single disease, we incorporate multiple illnesses for our study. By uncovering distinct patterns across surgical versus nonsurgical illnesses, we offer insight into a plausible mechanism that leads to frictions in teleconsultation flows. Similarly, our context of paid medical service allowed us to utilize price variations to investigate additional underlying mechanisms of the observed friction.

Exciting avenues could extend this research. First, although we investigated teleconsultation's role in reducing offline resource disparity in China, it would be useful to conduct similar analyses in different countries. From such studies, we can learn how fundamental differences between countries (e.g., cultural, financial, or regulatory differences) may affect physicians' and patients' use of teleconsultation services. To illustrate, in countries where more stringent regulations hinder the free flow of virtual care, we expect to see more substantial geography friction. For instance, in the United States, physicians can treat patients only in the state where the physicians' are licensed. Such a geographic restriction would serve as an additional obstacle to distant virtual care. Stronger distance constraints in virtual care may also reduce the rebalancing impact of telemedicine on offline resource disparity. Although an initiative (e.g., the Interstate Medical Licensure Compact) is actively trying to clear the license restriction, because of stakeholders' pushback, experts state that it may take time to clear the regulatory obstacle completely. Consequently, we ask readers to interpret our results with caution; that is, our findings may be more applicable to countries with a nationwide physician license. To the best of our knowledge, most countries issue a nationwide physician license except for the United States. Similarly, more stringent geographic restrictions in insurance reimbursement are also expected to limit distant virtual care. Besides regulatory differences, other factors, such as whether a country is a developed or a developing country, may also moderate our findings. For instance, in the case of an income constraint mechanism, if an empirical context is a developed country, rural patients may be rich enough to afford urban physicians' high fees. Such contextual differences may or may not moderate our findings. We hope future studies answer these interesting empirical questions.

Second, it will be interesting to study how the delivery of healthcare through telemedicine affects actual health outcomes (e.g., mortality, length of stay in hospitals) of patients in rural areas. Ideally, increased healthcare access should improve various health outcomes in rural areas. Although we anticipate some challenges in causally answering such a question (e.g., controlling for improvements in various other factors such as medicine, equipment, and facilities), it will be a meaningful next step to evaluate the efficacy of teleconsultations in lowering health outcome discrepancies between urban and rural areas.

Third, it would be meaningful to study whether, and if so how, the COVID-19 pandemic has changed teleconsultation patterns. Many countries have made changes in telehealth policy to facilitate greater access to telemedicine during the pandemic. For instance, in March 2020, U.S. President Donald Trump signed the Coronavirus Preparedness and Response Supplemental Appropriations Act to expand reimbursement coverage for telehealth services. Several states have also waived the physician licensing restriction to cope with the COVID-19 pandemic. These factors are expected to positively impact the telemedicine market growth and patients' willingness to use telemedicine services, thereby possibly reducing the social, information, and geography frictions we observed in this study. We hope future research provides insights on how the COVID-19 disruptions affect overall teleconsultation patterns and their implications on offline healthcare disparity.

Finally, because of the technicalities and substantial computational cost, the valued ERGM estimates parameters based on a cross-sectional network. A cross-sectional study may suffer from reverse causality. To alleviate this concern, we ran a series of ERGMs using lagged network variables each year. A cross-sectional study may also have identification issues because it cannot leverage within subject variations over time. To check whether our results stay consistent after incorporating the region-pair variances across time, we conducted panel estimation using temporal ERGM. With advances of the ERGM method, we hope future research can utilize the ERGM to model dynamic networks with valued ties.

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Endnotes

[1] In the United States, a physician license is granted by a state or jurisdiction and is typically valid only within its issuing state/jurisdiction. However, telehealth policy is changing rapidly as a result of the COVID-19 pandemic. Some states have provided temporary licensing waivers because of the COVID-19 public health emergency to provide greater access to care. At this point, it is unclear whether these waivers will remain in place once the pandemic is

over. For recent developments, check the information at the National Telehealth Policy Resource Center (https://www.cchpca.org/telehealth-policy/cross-state-licensing).

[2] Even in developed countries such as the United States, rural Americans tend to be poorer: the average per capita income for all Americans in 2018 was $54,446, whereas rural per capita income lagged at $35,765 (Rural Health Information Hub 2020).

[3] Many Chinese hospitals require patients to purchase appointment tickets to meet physicians. Scalpers often secure these tickets illegally and resell them for a significantly higher price. Recently, this illegal practice was brought to public attention by a viral video of a young woman in Beijing raging against scalpers (see https://www.youtube.com/watch?v=K3lUF5XXnuw accessed January 28, 2016, (in Chinese)). In the video, a young woman furiously rails at scalpers at the lobby of the Guang'anmen Hospital in Beijing. She had been waiting for two days to get an admission ticket for her sick mother. Hospitals charge a 300-yuan ($45) fee for registration, but scalpers had taken all registration tickets and were reselling them at 4,500 yuan ($686) to patients in line (Reuters 2016). Despite such an excessive price, upper-middle-class patients, who can afford the price, often resort to the black market because the waiting time can be excessively long (e.g., many days) without a scalper's ticket.

[4] We want to note that the conceptual definition of the three frictions can be difficult to disentangle completely.

[5] The median outdegree of urban regions is 20, whereas that of rural regions is 1. By contrast, urban regions exhibit lower in-degree centrality (median: 5) than rural regions (median indegree centrality: 16).

[6] Table A in the online appendix provides the classification details.

[7] Although its capability to leverage temporal dependencies of network evolution is appealing, because of substantial computational complexity and cost, TERGM allows us to model only binary relationships (i.e., whether a tie is present or not). That is, in our research setting, a relationship between region *i* and region *j* can only be either present or absent. However, teleconsultation flows are not binary, as there are considerable variations in the strength of flows between regions. By dichotomizing, TERGM treats all flows over 0 effectively equal to each other and consequently loses a significant amount of information concerning the strength variation of flows. The only ERGM version that allows us to model networks with valued ties is the generalized ERGM for a valued network (valued ERGM), so we chose this model for our main analysis.

[8] The ideal offline data set would be the one that captures the frequency of offline medical consultations between all potential pairs of regions, just like our telemedicine consultation data. Unfortunately, such data are not available.

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