# Does Telemedicine Affect Physician Decisions? Evidence from Antibiotic Prescriptions

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Telemedicine has long been of interest to the U.S. general public. Yet, despite the advent of high-speed internet and mobile device technology, telemedicine did not reach its full potential until the COVID-19 pandemic spurred its unparalleled adoption. This sudden shift in the setting of healthcare delivery raises questions regarding possible changes in clinical decision-making. Using a unique set of patient-provider encounter data from the U.S. in 2020 and 2021, we examine the effect of telemedicine on antibiotic prescription errors for urinary tract infections. We consider two types of prescription errors: prescribing when not recommended by guidelines (type I errors) and not prescribing when recommended (type II errors). After accounting for potential endogeneity issues using provider fixed effects and an instrumental variable approach, we find a significantly lower likelihood of overall prescription errors (type I and II errors combined) with telemedicine relative to in-person encounters. We also find heterogeneous effects by a provider's patient volume and the patient-provider relationship. Further analyses show that the reduction in prescription errors is mainly attributable to type I errors, and that patient health outcomes are not compromised when care is delivered via telemedicine. Finally, we discuss managerial implications for the pharmaceutical and insurance industries, as well as policy implications for governments.

*Key words*: health IT, telemedicine, prescription error, antibiotics, COVID-19

## 1. Introduction

Telemedicine has long been of interest to the general public in the U.S. As early as 1994, the Department of Health and Human Services disbursed more than $7 million to fund research and pilot programs for telemedicine, with a focus on improving access to healthcare (Field et al. 1996). The advent and widespread uptake of high-speed internet and mobile device technology were expected to lead to rapid utilization of telemedicine, as the technological barrier was less of an issue. It was believed that mobile devices equipped with high-speed internet connectivity and a high-resolution camera could easily support telemedicine apps and facilitate seamless interactions between patients and providers. However, due to regulatory, financial, and cultural barriers, telemedicine did not reach its full potential (Rogove et al. 2012).

This landscape changed dramatically with the onset of the COVID-19 pandemic. The spread of the highly infectious respiratory virus forced many states to order lockdowns and suspend

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non-essential in-person healthcare visits. These policy changes led to as much as a 60% reduction in visits to ambulatory care practices early in the pandemic in the U.S.[1] The unprecedented global pandemic, combined with the existing technological foundation, spurred an unparalleled adoption of telemedicine. Patients were motivated to use telemedicine to fill prescriptions and consult with providers for non-life-threatening health issues in the safe environment of their homes. Providers saw telemedicine as an additional revenue source at a time when a large portion of revenue from in-person visits had disappeared almost overnight. The federal government temporarily loosened restrictions on provider licensing, health information privacy requirements, and prescription of controlled substances. Many state governments also mandated insurance plans to reimburse telemedicine services at the same rate as in-person visits, eliminating the payment disparity that had previously stymied telemedicine adoption (see Weigel et al. 2020 for more telemedicine policy changes around the pandemic). As a result of these changes, the proportion of telemedicine visits among primary care visits increased from 1.1% in Q2 of total 2018-2019 visits to 35.3% in Q2 of 2020 (Alexander et al. 2020).

This sudden shift in the setting of healthcare delivery raises questions regarding possible changes in clinical decision-making across various parts of the healthcare systems. For instance, one of the ongoing concerns related to telemedicine is whether providers' prescribing decisions have remained consistent. To explore this issue, our paper focuses on the specific topic of prescription errors, which have been a major concern in the U.S. healthcare system. Each year, prescription errors lead to 7,000 – 9,000 deaths, affect over 7 million patients, and cost the economy more than $40 billion (Tariq et al. 2021). In the case of antibiotic prescriptions, the CDC estimates that 50% of all outpatient antibiotic use is inappropriate.[2] Using data of more than 19 million outpatient antibiotic prescriptions in the U.S., Chua et al. (2019) find that 53.7% – 89.2% of the prescriptions are inappropriate or potentially inappropriate. Given the unprecedented modality shift in care delivery, changes might occur in provider-patient modes of communication means and behaviors, which could in turn affect the prevalence of antibiotic prescription errors. Therefore, our paper aims to examine a vital healthcare management question: *What is the impact of telemedicine on providers' prescribing decisions*? More specifically, *does telemedicine affect the likelihood of antibiotic prescription errors relative to in-person settings?*

We focus on antibiotic prescriptions for UTI patients for several considerations. According to the literature, antibiotic prescription error is a prevalent issue for patients with urinary tract infections (UTIs), and 46.7% of antibiotics prescribed were found to be inappropriate for UTI

[1] https://www.commonwealthfund.org/publications/2020/apr/impact-covid-19-outpatient-visits

[2] https://www.cdc.gov/antibiotic-use/data/outpatient-prescribing/index.html#f3

treatment (Clark et al. 2021). Through interviews with providers, we further learned that the standard treatment for a UTI is preemptive antibiotic prescription without the need for an in-person examination. Anecdotal evidence also suggests that UTI is a most common urological condition that can be treated via telehealth[3] and that UTI patients can get equally good care with telehealth.[4] It is worth noting that a provider may require a patient to visit a lab and provide a urine specimen to confirm the infection, but the initial evaluation and treatment – providing a prescription for antibiotics – can all be done through telehealth.[3] More importantly, because UTI is not directly related to COVID-19, our sample is less subject to concerns about patient selection and unobserved bias related to the pandemic.

We assembled UTI patient records between January 2020 and September 2021 from a national proprietary electronic health record (EHR) data source. The data contain diagnosis, procedure, and medication information, allowing us to compare prescriptions associated with telemedicine visits and in-person visits. We follow the outpatient antibiotic prescription guidelines (Chua et al. 2019) to identify prescription errors, and we consider two types of prescription errors in this study: prescribing when not recommended by guidelines (type I errors) and not prescribing when recommended (type II errors).[5]

The ordinary least squares (OLS) regression results show a statistically significant reduction (20.7%) in the likelihood of overall prescription errors (type I and II errors combined) in telemedicine visits compared to in-person visits. It is worth noting that unobserved factors may exist and affect the endogenous selection of telemedicine, which then biases our parameter estimate. For example, suppose uncomplicated and less error-prone UTI cases are more likely to be seen via telemedicine. In that case, we will find a spurious correlation between telemedicine visits and fewer prescription errors. To address this endogeneity concern, we employ an instrumental variable (IV)—the proportion of telemedicine visits within the same zip code as a focal patient—after controlling for time, provider, and patient-specific factors.[6] The IV estimate shows a larger reduction in the likelihood of prescription errors (45.3%), suggesting that the OLS estimate provides a more conservative measure. We also show that our results hold through a battery of robustness checks.

Our study also investigates heterogeneous effects of telemedicine by a provider's patient volume and the patient-provider relationship. We find a larger reduction in the likelihood of overall prescription errors among providers with higher past UTI-patient volume and new patients who have

[3] https://www.healthgrades.com/right-care/kidneys-and-the-urinary-system/7-bladder-and-kidney-conditions-treated-in-telehealth-visits

[4] https://www.goodrx.com/conditions/urinary-tract-infection/uti-treatment-without-doctor-visit

[5] There may be other types of errors, such as wrong dosages (e.g., prescribing a 14-day regimen instead of a 7-day regimen), wrong administration route, etc. Unfortunately, our data are not suitable to analyze such errors.

[6] Other studies such as Lu et al. (2018) and Sun et al. (2020) use similar IVs in the healthcare research.

no prior encounters with providers. We further show that the error reduction is primarily driven by the reduction in the likelihood of type I errors (i.e., prescribing when not recommended by guidelines). By contrast, we do not find any statistical difference in the likelihood of type II errors (i.e., not prescribing when recommended). Lastly, we show that patient outcomes (i.e., revisits due to UTI complications) are not compromised after telemedicine visits.

These findings have several implications. First, telemedicine is likely to become an integral part of healthcare delivery going forward, and our study offers important insights into the relationship between telemedicine and prescription errors. In this regard, the U.S. Congress is working to extend waivers for telemedicine to "*give experts and regulators an opportunity to gather more data on telehealth and fashion a far-reaching proposal with more evidence,*"[7] and our causal inference analysis contributes to the much-needed data evidence on telemedicine. Our findings on prescription errors imply that telemedicine may help reduce drug waste and perhaps drug abuse, and potentially associated healthcare costs. Second, our analyses on heterogeneous effects along providers' and patients' characteristics can inform government and commercial insurer decisions on the allocation of resources to target certain patient and provider segments for telemedicine expansion when prescription errors are an important consideration. Third, our results offer a better understanding of the public risk of this new healthcare technology innovation. In our study, patient health outcomes in telemedicine encounters, at least in the case of UTIs, do not statistically differ from those of in-person encounters. In other words, telemedicine does not degrade the quality of care in our sample, which supports telemedicine deployment and expansion to payers and patients.

The rest of the paper is organized as follows. We first provide an overview of related literature. We then develop the hypotheses, discuss the clinical setting and describe the data, empirical strategy, and results. After that, we explore heterogeneous effects, and we examine error types and patient health outcomes to gain further insights. Finally, we conclude with a general discussion and implications for the healthcare industry and policy makers.

## 2. Literature Review

This section presents relevant literature on health IT, telemedicine, and prescription decisions.

### 2.1. Health IT and Physician Practice

In 2009, the Health Information Technology for Economic and Clinical Health Act (HITECH) was signed into law, which provided more than 30 billion in stimulus funds to promote the adoption of health IT (Agarwal et al. 2010). Researchers have identified two related streams of research questions: health IT adoption and its impact. Our paper fits into the second stream, and more specifically, we connect health IT adoption and physician practice.

[7] https://www.washingtonpost.com/politics/2021/06/14/health-202-lawmakers-are-deciding-future-telehealth/

Early studies on health IT are primarily exploratory and qualitative. Through a national survey of 2,758 physicians, DesRoches et al. (2008) investigate how the adoption of electronic health records affects physician practices. Despite the relatively low adoption rate, physicians who adopted EHR systems reported positive effects on quality of care, including quality clinical decisions, communication with other providers and patients, prescription refills, timely access to medical records, and avoidance of medication errors. Besides the positive effect, literature also reports adverse effects, where the improper use of health IT might be harmful to physician practice and care quality. For instance, drawing on a literature review, Ash et al. (2004) find that the implementation of health IT seems to foster error, and the errors can happen either in the process of entering and retrieving information or in the communication and coordination process.

More recent research literature mainly relies on empirical studies and expands the scope in the settings and the aspects of physician practice. Goh et al. (2011) examine the interplay between health IT and patterns of clinical work. The findings suggest that the key to successful health IT implementation is to manage the co-evolution process between routines and HIT and to actively orchestrate a virtuous cycle through agentic action. Bhargava and Mishra (2014) study the impact of an EHR system on physician productivity. Using a panel data set comprising 87 physicians over 39 months in the US, the study finds that productivity drops sharply immediately after technology implementation and recovers partly over the next few months. Wang et al. (2020) investigate physicians' online-offline behavior dynamics using data from China. The study shows that physicians' online activities can lead to a higher service quantity in offline channels, whereas offline activities may reduce physicians' online services because of resource constraints. Ganju et al. (2020) examine the role clinical decision support systems (CDSS) play in attenuating systematic bias. The results suggest that CDSS adoption significantly shrinks disparities in amputation rates across white and black patients, which is driven by changes in treatment care protocols that match patients to appropriate specialists, rather than altering within physician decision making. Li et al. (2021) investigate the value of HIT interoperability in the interhospital transfer process of heart attack patients. The authors find health IT interoperability has little effect in reducing duplicate electrocardiogram testing. However, better HIT interoperability yields a 15.6% more reduction in the throughput time and leads to a three-percentage-point decrease in the 30-day readmission rate of transferred patients. Huang et al. (2021) examine the effect of online-offline service integration on e-healthcare providers. The study shows that the service integration function increases providers' online demand and reputation but decreases offline demand.

## 2.2. Telemedicine

### 2.2.1. *Telemedicine and Its Application*

Telemedicine generally refers to the delivery of care at a distance, where a provider in one location uses a telecommunications infrastructure to deliver care to a patient at a distant site.[8] Because of the slow telemedicine adoption before the pandemic, the literature has often focused on identifying barriers to adoption. For example, Lin et al. (2018) point out that rural location, operational factors, patient demographic characteristics, and reimbursement policies are the major barriers to telemedicine among federally funded health centers in the U.S. Kruse et al. (2018) conduct a systematic review of studies worldwide and identify barriers such as technically challenged staff, resistance to change, cost and reimbursement, and patient demographics. Hwang et al. (2021) find that social and information frictions, such as cultural and linguistic differences and limited media coverage, suppress the supposedly free flow of teleconsultations across different regions in China. Many of these barriers came down in a matter of weeks during the pandemic (such as the lift of restrictions on reimbursement), and one may wonder if any barriers remain. McCullough et al. (2021) further use data from Michigan during the pandemic and find that the accelerated adoption may have depended on broadband access and technology skills, exacerbating disparities in healthcare.

Another stream of research investigates the impact of telemedicine adoption on healthcare utilization and workload. Ayabakan et al. (2020) study the impact of telehealth use on utilization and find a substitution effect of telehealth for chronic patients and a gateway effect for non-chronic patients. Rajan et al. (2019) find that with the introduction of telemedicine, the specialists become more productive and the overall social welfare increases, although some patients, unexpectedly, will be worse off. Saghafian et al. (2018) develop a partially observable Markov process to study the effectiveness of telemedical physician triage in workload management, and then conduct analytic and numerical analyses to derive insights into the management of the telemedical physician triage system. Sun et al. (2020) focus on the emergency room setting and find that telemedicine can improve provider productivity and reduce emergency room congestion. Bavafa et al. (2018) and Bavafa and Terwiesch (2019) find the e-visit channel (i.e., secure messaging in their context) increases patient visits and provider workload. Delana et al. (2019) find telemedicine reduces hospital visit rates but increases overall network visit rates.

As Royce et al. (2020) pointed out, one of the foremost concerns during the rapid adoption of telemedicine is maintaining safety and quality of care. However, limited research has connected telemedicine and physician practice, partly due to the low telemedicine adoption rate before the

[8] https://www.aafp.org/news/media-center/kits/telemedicine-and-telehealth.html

pandemic. Therefore, our study aims to investigate the effect of telemedicine on physician prescription errors and patient health outcomes, which we believe is critical before its broader application and extension.

#### 2.2.2. *Telemedicine and Antibiotic Prescription Errors*

A small number of papers in the medical literature have examined the relationship between telemedicine and antibiotic prescription errors, but the evidence thus far is equivocal, with prior research reporting positive, negative, and nonexistent effects. Some studies find that telemedicine visits, relative to office visits, are associated with more inappropriate antibiotic prescriptions and more broad-spectrum antibiotic use among adults and children (Mehrotra et al. 2013, Ray et al. 2019, Uscher-Pines et al. 2016). By contrast, Shi et al. (2018) and Yao et al. (2020) do not find statistical differences in antibiotic prescriptions between the two settings, whereas Hersh et al. (2019) find fewer antibiotic prescriptions among telemedicine visits for children under 18 years of age.

Although the varying conclusions may be attributable to differences in the data sample and time period, the most critical issue in these studies is the lack of consideration for potential endogeneity issues related to telemedicine adoption and usage. Besides, these studies are typically based on individual hospitals that are early adopters that pioneer in health IT initiatives. Thus their systems tend to be customized and optimized for the clinical setting. However, in practice, patients' unobserved health conditions may sway providers' decisions to choose telemedicine over office visits, and different policies may hinder some providers from adopting it. Hence, a more general sample of physicians and causal inference is critical to properly justify the impact of telemedicine on physician clinical decisions.

Given the lack of clear evidence and the ethical concerns of conducting large-scale randomized experiments in healthcare settings, causal inference from observational data is critical for academia and healthcare practitioners. As such, our paper aims to address the endogeneity issues associated with telemedicine visits and draw a causal link between telemedicine use and antibiotic prescription errors. Besides accounting for provider heterogeneity, patient characteristics, and time-fixed effects, we apply the IV estimation. Similar IV approaches have been employed to address endogeneity concerns related to technology adoption in the healthcare market. Dranove et al. (2014) show that an organization's adoption of healthcare technology depends on the local market's adoption, because local users share the adoption costs. This finding led Lu et al. (2018) to construct an IV based on the local hospitals' technology adoption rate. Sun et al. (2020) also use a similar IV to address endogeneity issues related to telemedicine use in emergency rooms. Unlike these studies in which the technology use is examined at the institution level, we observe telemedicine use at the encounter level. Therefore, we construct an IV based on telemedicine use among neighboring individuals in the vicinity. Details on IV construction and IV validity are discussed in section 5.2.

Further differentiating our work from the existing literature, we disentangle type I and type II errors that can inform different healthcare policy implications. We also examine the heterogeneous effects of telemedicine to gain insights into the moderating role of patient volume and patient-provider relationships that the previous literature did not offer. Moreover, we investigate patient health outcomes to assess the effect of provider prescribing decisiveness on care quality.

## 3. Hypothesis Development

The main objective of this study is to examine whether and in what direction telemedicine affects provider prescription errors in the case of antibiotics. Towards this goal, we develop three hypotheses in this section to conceptualize the mechanisms through which telemedicine may affect provider prescribing decisions.

Health information technology has generally been shown to improve healthcare delivery in various respects, such as quality, efficiency, and provider satisfaction (Buntin et al. 2011). Telemedicine is no different. Compared with conventional face-to-face encounters, virtual care delivery can potentially enhance the provider prescription decision process and reduce the likelihood of prescription errors through three main channels.

First, the telemedicine channel can facilitate providers' access to medication information, which will help reduce prescription errors. Evidence suggests that providers are able to collect additional medical information about patients that would have been difficult to obtain during an office visit. Based on a series of interviews with providers, Gomez et al. (2021) report that medication reconciliations are easier to conduct via telemedicine because "*patients can show you their medications, read the labels,*" whereas patients often do not recall their medication names and regimens in office settings. Powell et al. (2017) also note that another advantage of telemedicine is the ability to incorporate information from caregivers and family members who would not have been present in an office visit. These individuals may provide additional information about the medication history of the patient as well. When more drug information is provided by patients via telemedicine, this may sway providers to check prescribing guidelines more carefully to avoid potential drug interactions, thereby leading to lower prescription errors.

Second, both the literature and anecdotes suggest that telemedicine helps streamline provider workflows. For instance, William Morris, Cleveland Clinic's associate chief information officer, says that "when providers can answer questions and review tests remotely, it is more efficient for the provider, the practice, and the patient."[9] Compared with office visits, providers do not

[9] https://www.medicaleconomics.com/view/how-telemedicine-expansion-will-affect-physician-practices

need to move from one patient examination room to another, so they can better concentrate on taking care of patients (Sun et al. 2020). Moreover, the U.S. Department of Health and Human Services suggests that Electronic Health Records (EHR) should be easy to incorporate into the telehealth workflow,[10] enabling providers to address patient needs with patient records at hand. Hence, providers can comprehensively review patients' health conditions seamlessly, with minimal distractions from other administrative tasks, which can help reduce errors in judgment and hence prescription errors.

Third, telemedicine allows patients to receive care in a more private and comfortable environment, thus positively contributing to their willingness to communicate with providers and help improve information coordination. For instance, Powell et al. (2017) find that many patients feel more comfortable with video visits than office visits and prefer telemedicine because they can receive care in relaxed surroundings with supportive people. Further, during the pandemic, a "face-to-face" telemedicine visit may better facilitate communication than is possible in a "mask-to-mask" office visit, which can also enhance patient-provider communication and lead to improved prescription decisions.

While telemedicine seems to have great potential for improving providers' prescriptions decisions, in practice, these visits may have unintended consequences, either due to technical difficulties or frictions associated with coordination issues (such as access to the appointment and lack of coordination in the virtual waiting room). When these occur, telemedicine visits might be inferior to in-person encounters. As suggested by Serrano and Karahanna (2016), technology capabilities are critical in e-consultations. The extent to which e-consultation technology can simulate direct patient contact experiences and transmit relevant information to the provider will influence e-consultation diagnostics. When delivering care via telemedicine, technology limitations may hinder providers' ability to acquire sensory information, which is only available when performing physical evaluations (Miller 2003). Accordingly, providers may not detect certain patient symptoms that they are trained to look for in their medical training and residency, which may lead to worse prescription decisions. Moreover, the effective use of telemedicine requires IT training and workflow restructuring for both patients and providers. However, because the COVID-19 pandemic was unforeseen, it is likely that both providers and patients lack systematic training before using telemedicine at scale. This lack of training on each side may prevent effective patient-provider coordination and service outcomes.

Conditioning on the above argument, whether telemedicine can improve providers' prescribing decisions is ultimately an empirical question. We, therefore, propose the following hypothesis for an empirical test.

[10] https://telehealth.hhs.gov/providers/planning-your-telehealth-workflow/

**Hypothesis 1:** *Telemedicine leads to better prescribing decisions* (*measured by a decreased likelihood of antibiotic prescription errors*).

The effect of telemedicine may differ by a provider's patient volume (i.e., patient treated per period). Kc et al. (2020) note that period-specific volume is related to the scale of medical practice, and this can affect care processes and patient outcomes. Existing studies have shown that a larger scale of practice (i.e., higher volume of patients) is often associated with a higher quality of care, such as reduced length of stay and lower mortality rates (Kc and Terwiesch 2011, Clark and Huckman 2012, Kuntz et al. 2019). Therefore, it is reasonable to assume that the scale at which a provider sees patients may influence the effect of telemedicine. For example, compared to less experienced providers, providers who are used to seeing a high volume of UTI patients may face fewer difficulties in diagnosing and treating the infection. This difference could be more salient in a virtual setting where technological limitations prevent doctors from performing a physical examination and retrieving other tactile information. In other words, the care processes that change via telemedicine can potentially improve prescribing decisions more for providers with a higher patient volume, as these providers can make better use of the improved information, and be less affected by limitations due to technology-related issues. Accordingly, we posit the following hypothesis:

**Hypothesis 2:** *The effect of telemedicine is larger, in terms of a larger reduction in antibiotic prescription errors, when the care is delivered by providers with a higher patient volume.*

The effect of telemedicine on prescription errors may also rely on the patient-provider relationship. More specifically, the effect may be smaller for established patients than for new patients for three reasons. First, existing studies find familiarity is associated with fewer errors (Asare and McDaniel 1996). In the case of in-person encounters, providers who are more familiar with established patients, can communicate efficiently with them on their medications and health conditions, and thus are less prone to prescription errors in in-person settings. As a result, the marginal benefit of telemedicine to established patients will be smaller than that to new patients. Second, existing patients' health information is generally available in EHR, so providers are better aware of their medications and health conditions. By contrast, providers have little information about new patients, the additional medication information provided by established patients via telemedicine is thus less informative than that provided by new patients. Therefore, when providers administer prescriptions, the marginal benefit from telemedicine is likely smaller for established patients. Finally, according to Gomez et al. (2021), in a virtual setting, it may be easier for providers to deny a patient's requests for antibiotics when deemed unwarranted. In their study, one provider stated that she feels comfortable rejecting patients' unwarranted superfluous requests for certain medications because "*they have a video in front of them instead of the person's right there yelling at me.*" Given the relative ease of rejecting a prescription request, telemedicine will significantly reduce the likelihood of prescription error for new patients, who are more likely to test the provider's willingness to prescribe antibiotics. Therefore, we posit the following hypothesis:

**Hypothesis 3:** *The effect of telemedicine is larger, in terms of a larger reduction in antibiotic prescription errors, when there is no established patient-provider relationship.*

## 4. Clinical Setting and Data

In this section, we provide details on the clinical setting and summarize our data.

### 4.1. Clinical Setting: UTIs and Prescription Errors

We use UTIs as our research context for several reasons. First, UTI is one of the common reasons to seek care in the U.S., resulting in more than eight million outpatient visits and one million emergency department visits annually, with associated costs estimated to be over $2 billion per year (Rastogi et al. 2020). Second, after conducting several interviews with providers, we find that UTI is a condition that can be easily diagnosed and treated regardless of the care setting. For example, the initial treatment of UTIs would be prescribing antibiotics in both virtual and in-person settings. Therefore, channel selection would be less of a concern than for other conditions that require a physical examination, such as ear infections. This assumption is confirmed by the Infectious Diseases Society of America (IDSA) guidelines that recommend presumptive antibiotics to treat suspected UTI cases (Gupta et al. 2011). Third, because our data come from the pandemic period, we rule out conditions related to COVID-19 symptoms. For instance, even though acute respiratory infection is often treated via telemedicine, patients with such symptoms may be asymmetrically directed to either telemedicine or the emergency department, depending on the patient's condition, the state of the pandemic, and the availability of hospital beds. Comparatively, UTIs are less likely to suffer from the pandemic-related selection. Last, because we study the quality of care in terms of prescription errors, we need clear guidelines that we can compare against observed prescriptions. Fortunately, clinical guidelines of antibiotic prescriptions are readily available. A recent publication by Chua et al. (2019) provides a comprehensive classification scheme to determine whether each of more than 91,000 International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) diagnosis codes "always," "sometimes," or "never" justifies an antibiotic prescription. Based on patients' diagnosis codes and the medication administered by providers, we follow Chua et al. (2019) to determine whether an antibiotic prescription is appropriate.

Antibiotic prescriptions have long been scrutinized by healthcare officials because of the possibility of antibiotic resistance. CDC calls it "*one of the biggest public health challenges of our time*" with more than 2.8 million people getting an antibiotic-resistant infection, and over 35,000 people dying annually.[11] Antibiotic prescription errors can increase antibiotic resistance among the

[11] https://www.cdc.gov/drugresistance/index.html

population, and CDC has been encouraging providers to follow clinical and treatment guidelines by launching antibiotic stewardship programs for various care settings. Although prescribing antibiotics when not recommended can lead to long-term antibiotic resistance, not prescribing them when recommended is also concerning because patients are at the risk of undertreatment, which can lead to revisits or potentially serious complications that could have been mitigated with appropriate prescriptions.[12] Unfortunately, the short span of our data does not allow us to investigate long-term antibiotic resistance. Instead, we examine patient health outcomes related to the possibility of undertreatment and related complications shortly after prescriptions.

### 4.2. Data Description and Preparation

We obtain proprietary encounter-level EHR data in the U.S. Our data have several unique features. First, they include modifiers appended to the Current Procedural Terminology (CPT) or the Healthcare Common Procedure Coding System (HCPCS) codes for each encounter, which allows us to distinguish telemedicine from in-person visits. More specifically, our data record encounters conducted via telemedicine with one or more of the following modifiers: (1) 95–synchronous telemedicine (two-way live audiovisual), (2) GT–interactive audio and video telecommunications, (3) GQ–asynchronous telecommunication system, and (4) G0–telemedicine services for diagnosis, evaluation, or treatment of symptoms of an acute stroke.[13]

Second, our data contain detailed information about diagnoses and medications for each visit. The diagnosis codes help us identify UTI-related encounters (ICD-10-CM: O23, O86.2, O03.38, O03.88, O04.88, O07.38, O08.83, N30.0, N30.8, N30.9, N34.1, N34.2, or N39.0). Each included UTI encounter has the prescribing provider's identification information and medication codes. The medication codes allow us to identify whether a prescription error exists and if so, what type of error it is, given the diagnoses. The main outcome variable is denoted as $PrescriptionError$, a binary variable indicating whether the prescribed medication meets the guideline for an encounter. More specifically, for each encounter, we compile a complete list of diagnoses pertaining to the visit. For each diagnosis, we refer to outpatient antibiotic prescription guidelines (Chua et al. 2019) and define an antibiotic prescription as "appropriate" or "inappropriate". At the encounter level, we then aggregate the guideline recommendations across all diagnoses and define antibiotic prescription as not recommended, if at least one diagnosis is inappropriate for an antibiotic prescription. Finally, we compare this guideline recommendation with the actual antibiotic administered to the patient and define $PrescriptionError = 1$ if the actual prescription does not match the guideline recommendation, and $PrescriptionError = 0$ otherwise.

[12] https://www.wsj.com/articles/SB10001424052702303678404579536284129494564

[13] https://www.cms.gov/outreach-and-educationoutreachffsprovpartprogprovider-partnership-email-archive/2020-04-03-mlnc-se

Third, our data contain various patient characteristics, including patient demographics and health conditions (e.g., patient age, gender, and diagnoses). We also observe whether the patient is pregnant or not. This is relevant because pregnant patients require a different antibiotic regimen (Ailes et al. 2018). We also collect information on patient comorbidity. The extant literature has widely used the Elixhauser comorbidity index to control for the severity of patient health status (see, e.g., Elixhauser et al. 1998, Berry Jaeker and Tucker 2017, Bartel et al. 2020). We follow these studies to calculate the Elixhauser comorbidity index by first identifying relevant comorbidities using the list of diagnosis codes of an encounter and then calculating the weighted sum of these comorbidities.

Fourth, our data include unique patient and provider identifiers, which allows us to quantify the familiarity between a patient and a provider. We follow the CPT definition[14] and construct $EstablishedPatient_i$ as 1 if a patient has seen the same provider within three years prior to encounter $i$, and 0 otherwise. Distinguishing established from new patients is critical, because a provider has different levels of prior information about different patients, which can also affect the likelihood of prescription errors.

Provider and patient identifiers are also useful in conducting empirical analyses. Provider identifiers allow us to include provider fixed effects and account for time-invariant provider heterogeneity when we analyze the effect of telemedicine on prescription errors. In the sample construction, we focus on providers who have prescription records for at least two encounters during the sample period. The availability of patient identifiers enables us to track patients over time and analyze the effect of telemedicine on health outcomes such as 7- or 30-day revisits related to severe UTI complications, such as pyelonephritis (ICD-10-CM: N10) and urosepsis (ICD-10-CM: A41 and N39.0).

### 4.3. Summary Statistics

Table 1 provides summary statistics of our data sample, containing 14,305 in-person encounters and 1,769 telemedicine counters between January 2020 and September 2021. Our main outcome variable, $PrescriptionError$, has a mean of 0.668 and a standard deviation of 0.471 for all encounters (see column"All Encounters"). This summary statistic of prescription errors is consistent with existing studies. For example, Chua et al. (2019) study antibiotic prescriptions for outpatients and find 53.7% – 89.2% of the prescriptions are inappropriate or potentially inappropriate. Comparing columns "In-person" and "Telemedicine", we see the average likelihood of prescription errors is 0.698 (standard deviation of 0.459) for the encounters conducted in person and 0.425 (standard

[14] CPT defines an established patient as "one who has received a professional service from the physician/qualified healthcare professional or another physician/qualified healthcare professional of the exact same specialty and subspecialty who belongs to the same group practice, within the past three years." Please see `https://www.aapc.com/blog/37138-how-to-determine-new-vs-established-patient-status/` for more details.

deviation of 0.494) for the encounters conducted via telemedicine. The statistically significant t-test (see column "T-Test") suggests that visits via telemedicine are less likely to have prescription errors than those conducted in person. This comparison lends model-free support for Hypothesis 1. However, the difference might not be a causal reflection of telemedicine utilization. For instance, patients with lower risks could be more likely to use telemedicine, and these patients are less subject to prescription errors, because of their uncomplicated conditions. We account for such confounding factors in the regression models in section 5.

**Table 1 Summary Statistics**

| Variable | All Encounters | | In-person | | Telemedicine | | T-Test | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | t | $p > \|t\|$ |
| Dependent Variable | | | | | | | | |
| Prescription Error | 0.668 | 0.471 | 0.698 | 0.459 | 0.425 | 0.494 | 23.399 | 0.000 |
| Independent Variable | | | | | | | | |
| Patient Age | 45.869 | 21.168 | 46.148 | 21.261 | 43.616 | 20.263 | 4.750 | 0.000 |
| Patient Female | 0.899 | 0.302 | 0.897 | 0.304 | 0.914 | 0.280 | -2.278 | 0.023 |
| Patient Pregnant | 0.015 | 0.121 | 0.015 | 0.123 | 0.009 | 0.095 | 2.109 | 0.035 |
| Patient with Comorbidity | 0.337 | 0.473 | 0.354 | 0.478 | 0.199 | 0.399 | 13.103 | 0.000 |
| Established Patient | 0.284 | 0.451 | 0.289 | 0.453 | 0.246 | 0.431 | 3.754 | 0.000 |
| Number of Observations | 16,074 | | 14,305 | | 1,769 | | | |

Note: This table reports the summary statistics of the data utilized in the regression analyses. Dependent variable is the likelihood of overall prescription errors (type I and type II combined). T-test compares variable mean between telemedicine and in-person encounters.

The lower part of Table 1 summarizes the key independent variables on patient characteristics. Female patients account for the majority of UTI visits, with approximately 90% visits for both in-person and telemedicine encounters. We also notice that the two groups are slightly different along several dimensions. Patients seen in person, on average, are older, have a higher pregnancy rate, tend to have comorbidities and established patient-provider relationships compared with patients using telemedicine. These differences suggest the treatment (i.e., telemedicine) is not randomly assigned to patients, and controlling for patient heterogeneity is important when analyzing the effect of telemedicine on prescription errors. This comparison also reinforces the importance of addressing patient and provider selection using instrumental variable analysis, because the control and treatment groups may also potentially differ across unobserved patient characteristics.

## 5. Empirical Strategy

In this section, we first discuss the empirical model that can be used to check the relationship between prescription error and telemedicine. We then illustrate our approach to addressing potential endogeneity issues.

### 5.1. Empirical Model

Our dependent variable is $PrescriptionError_i$, a binary variable that is equal to 1 if the prescribed medication does not meet the guideline for encounter $i$ (i.e., either type I error or type II error), and is equal to 0 otherwise. Note an encounter may have multiple diagnoses. In the main analysis, we consider an encounter as having a prescription error if a mismatch exists between the actual prescription and the guideline recommendation based on any diagnosis of a visit. As a robustness check, we consider alternative definitions of prescription error by calculating the fraction of diagnoses with inappropriate prescriptions in section 6.2.5.

The independent variable of primary interest is $Telemedicine_i$, which is equal to 1 if encounter $i$ is conducted via telemedicine, and 0 if conducted in person. As discussed in section 4.2, we are able to separate the two modalities because our data have CPT codes that allow us to determine whether an encounter is conducted via telemedicine. Note the use of telemedicine varies widely across providers and patients and over time. The same provider may see some patients via telemedicine and others in person. We also include a broad range of patient demographics and health conditions (i.e., patient age, gender, pregnancy status, and Elixhauser comorbidity index) as well as a proxy for the familiarity between a patient and a provider ($EstablishedPatient_i$) as covariates.

Finally, we include a set of provider fixed effects (denoted by $Provider_i$) to control for systematic differences across providers. Provider fixed effects control for all time-invariant characteristics, including provider demographics and other unobserved factors that might correlate with their predispositions to use telemedicine or prescription decisions. We include a set of year-month fixed effects (denoted by $Time_i$) to control for the time trends of prescription errors. This approach is motivated by the existing studies (see, e.g., Cliff 2014) that find more medical errors in July when medical school graduates begin residencies.[15]

In the main analysis, we use a linear probability model. The relation between the dependent and independent variables can be described using equation (1):

$$PrescriptionError_i = \alpha_0 + \alpha_1 Telemedicine_i + \alpha_2 X_i + \alpha_3 Provider_i + \alpha_4 Time_i + \epsilon_i, \qquad (1)$$

where the sample is constructed at the encounter level $i$. $X_i$ denotes a set of patient characteristics and the familiarity between the provider and patient for an encounter $i$, and $\epsilon_i$ denotes the error term. We choose the linear probability model for two reasons. First, as Angrist and Pischke (2008) note, linear probability models are easy to interpret and produce results similar to those obtained using nonlinear models such as probit. Second, as Goldfarb and Tucker (2011) point out, estimating a probit model with a large set of provider fixed effects is computationally limiting. Nonetheless,

[15] Using alternative time fixed effects does not change the main conclusion of this study. See section 6.2.4 for more details on robustness checks using alternative seasonality.

we use a probit model as a robustness check and re-estimate the effect of telemedicine in Section 6.2.1. All results are consistent with the linear probability model.

### 5.2. Identification

Estimating equation (1) using OLS regression poses challenges to interpreting $\alpha_1$ as a causal effect, because unobserved factors may affect both the decision to use telemedicine and the likelihood of prescription errors.

From the provider side, systematic differences across providers can bias our estimates. Although provider fixed effects will account for unobserved time-invariant provider heterogeneity, and the year-month fixed effects will capture the common telemedicine-use trends as the pandemic progresses and government policy changes, unobserved time-varying provider characteristics may still exist, leaving potential endogeneity issues. Moreover, patients with high-risk factors (who are often more difficult to diagnose) may be *less* likely to be scheduled for telemedicine, because providers prefer to examine these patients in person to gather more information and build a better clinical rapport with the patients. In that case, the OLS estimate will bias the true effect of telemedicine. On the other hand, patients with high-risk factors may be *more* likely to be scheduled for telemedicine, due to the lack of mobility or concerns about COVID-19 infection, which again biases the true effect of telemedicine.

To address these potential endogeneity issues, we use the neighboring telemedicine use in the vicinity as an IV. More specifically, for encounter $i$, we first identify all encounters in the past two weeks within a focal patient's zip code. We then calculate the fraction of encounters conducted via telemedicine (denoted by $NeighborTelemedicine_i$) and use it as an IV.[16] Similar IVs have been employed to study technology adoption in the healthcare market. For example, Lu et al. (2018) and Sun et al. (2020) use the neighboring technology adoption rate as an IV for a focal institution's adoption.

A valid IV needs to satisfy two conditions: (1) It must be correlated with the endogenous variable (i.e., the relevance condition) and (2) it must be uncorrelated with the error term conditional on covariates (i.e., the exclusion restriction). Our IV is likely to satisfy the relevance condition because a focal patient's use of telemedicine is likely to correlate with neighboring patients' telemedicine adoption, due to similar local service provision from neighboring providers, government initiatives, or IT infrastructure. We formally show the positive relationship between the two in the first-stage regression. Note that our model includes patient characteristics, provider fixed effects, and time fixed effects. Therefore, the exclusion restriction is that the IV is not correlated with the

[16] Our estimation remains robust when using alternative periods (e.g., 1 or 3 weeks) or an alternative definition (e.g., excluding the focal provider's encounters) to construct IV. Results are available upon request.

likelihood of antibiotic prescription errors for UTI encounters after controlling for these covariates. One may be concerned that provider fixed effects are insufficient to control for unobserved time-changing factors underlying the use of telemedicine, because the COVID-19 pandemic may have a disproportionate impact across regions over time. Therefore, we include the local COVID-19 infection cases as additional control and check the robustness of our results in section 6.2.2.

We use two-stage least squares regressions to estimate the effect of telemedicine on prescription errors. In the first stage, we regress the endogenous variable, $Telemedicine_i$, over the IV, $NeighborTelemedicine_i$, and other independent variables. That is,

$$Telemedicine_i = \beta_0 + \beta_1 NeighborTelemedicine_i + \beta_2 X_i + \beta_3 Provider_i + \beta_4 Time_i + \xi_i, \tag{2}$$

where $\xi_i$ denotes an error term. The coefficient $\beta_1$ indicates the relation between the IV and the endogenous variable. A positive and statistically significant coefficient would suggest that our IV has sufficient explanatory power for the endogenous variable. We use the first-stage regression to predict the endogenous variable (denoted by $\widehat{Telemedicine_i}$).

In the second stage, we regress the dependent variable, $PrescriptionError_i$ over the predicted endogenous variable, $\widehat{Telemedicine_i}$, and other independent variables. That is

$$PrescriptionError_i = \gamma_0 + \gamma_1 \widehat{Telemedicine_i} + \gamma_2 X_i + \gamma_3 Provider_i + \gamma_4 Time_i + \zeta_i, \tag{3}$$

where $\zeta_i$ denotes the error term. We are particularly interested in the coefficient $\gamma_1$. A positive coefficient would suggest that telemedicine increases the likelihood of prescription errors, whereas a negative coefficient would suggest the opposite. Comparing $\alpha_1$ in equation (1) and $\gamma_1$ in equation (3) allows us to better understand the direction of the potential bias due to endogeneity issues.

## 6. Results

In this section, we show results from our analyses and perform a battery of robustness checks to analyze the sensitivity of our results to various endogeneity concerns.

### 6.1. Main Results

Before presenting the main results, we check the relevance condition of the IV. Table 2 summarizes the results from the first-stage regression. The coefficient of the IV, $NeighborTelemedicine$, is significantly different from zero at the 1% significance level. The resulting first-stage F-statistic is 99.20, suggesting that our IV has sufficient explanatory power. The positive coefficient implies that the likelihood of telemedicine usage by an individual and her/his neighbors goes in the same direction. Consistent with the summary statistics, we find that patients with comorbidity are less likely to be seen via telemedicine, perhaps because providers prefer to see them in person to gather more information about other health conditions and complications that these patients may have.

**Table 2 Results from the First-stage IV Regression**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Neighbor Telemedicine | 0.648∗∗∗ | 0.065 |
| Patient Age | 0.0002∗ | 0.0001 |
| Patient Female | −0.020∗∗∗ | 0.007 |
| Patient Pregnant | −0.032 | 0.026 |
| Patient with Comorbidity | −0.053∗∗∗ | 0.007 |
| Established Patient | 0.007 | 0.007 |
| Provider Fixed Effects | Included | |
| Month Fixed Effects | Included | |
| Number of Observations | 16,074 | |
| R-Squared | 0.052 | |
| F-Test of Excluded Instruments | 99.20*** | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the first-stage of IV regression. The dependent variable is a binary indicator for telemedicine. Independent variables are the IV, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

The results from the second-stage IV regression are summarized in Table 3. The coefficient of $Telemedicine$ is negative and significantly different from zero at the 1% significance level, which suggests that the use of telemedicine reduces the probability of prescription errors, thereby supporting Hypothesis 1. A coefficient of $-0.453$ suggests that the use of telemedicine reduces the likelihood of overall prescription errors by 45.3%. As we discussed in the hypothesis development, the improved prescription decision via telemedicine may be driven by factors such as better information provided by patients on existing medication, improved provider workflow, and better patient-provider communication in virtual settings as opposed to in-person settings.

**Table 3 Results from the IV Regression**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Telemedicine | −0.453∗∗∗ | 0.136 |
| Patient Age | −0.0002 | $<0.0003$ |
| Patient Female | 0.058∗∗∗ | 0.016 |
| Patient Pregnant | 0.018 | 0.040 |
| Patient with Comorbidity | 0.066∗∗∗ | 0.015 |
| Established Patient | −0.083∗∗∗ | 0.011 |
| Provider Fixed Effects | Included | |
| Year-month Fixed Effects | Included | |
| Number of Observations | 16,074 | |

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table summarizes the results from the second-stage of IV regression. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

As a comparison, Table 4 summarizes the results from the OLS regression. We see that the coefficient of $Telemedicine$ is negative and significantly different from zero at the 1% significance level, which also supports Hypothesis 1. However, we note that the coefficient from the OLS regression (i.e., $-0.207$) is smaller in magnitude than that from the IV regression, implying that unobserved patient or provider factors that potentially increase the likelihood of prescription errors are positively correlated with telemedicine. For instance, patients with high-risk factors are more likely to use telemedicine due to mobility issues or concerns about COVID-19 infections, and these patients are more prone to prescription errors because of their complex cases. Therefore, one will underestimate the effect of telemedicine without accounting for potential endogeneity issues in the data.

**Table 4 Results from the OLS Regression**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Telemedicine | $-0.207$*** | 0.021 |
| Patient Age | $-0.0003$ | 0.0003 |
| Patient Female | $-0.053$*** | 0.015 |
| Patient Pregnant | 0.025 | 0.042 |
| Patient with Comorbidity | 0.079*** | 0.013 |
| Established Patient | $-0.085$*** | 0.011 |
| Provider Fixed Effects | Included | |
| Year-month Fixed Effects | Included | |
| Number of Observations | 16,074 | |
| Adjusted R-Squared | 0.210 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the OLS regression. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

### 6.2. Robustness Checks

In this section, we analyze the sensitivity of our results by performing five robustness checks. The first robustness check uses an alternative empirical model. The second robustness check includes COVID-19 infections as an additional control. The third robustness check controls for unobserved time-invariant and time-varying patient local factors. The fourth robustness check includes alternative seasonality controls. The final robustness check uses an alternative definition of prescription errors.

#### 6.2.1. *Alternative Model Specification*

In the main analysis, we use the linear probability model to estimate the effect of telemedicine. Given that the dependent variable is binary, we use an IV probit model to re-estimate the effect of telemedicine to alleviate concerns of estimation bias due to model selection. The results from this robustness check are summarized in Table 5. We see the coefficient of $Telemedicine$ is negative and significantly different from zero at the 1% significance level. Note the coefficient from the probit model is difficult to interpret directly. Therefore, we calculate the marginal effect at the mean and find that the estimate (i.e., $-0.444$) is similar to the average effect (i.e., $-0.453$) from the linear probability model in Table 3. The result corroborates the validity of the linear probability model in the main analysis.

**Table 5 Results from the IV Regression (Probit Model)**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Telemedicine | $-1.384***$ | 0.290 |
| Marginal Effect | $-0.444***$ | 0.091 |
| Patient Characteristics | Included | |
| Provider Fixed Effects | Included | |
| Year-month Fixed Effects | Included | |
| Number of Observations | 15,051 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV probit model. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider. The reduction in the number of observations is due to dropped providers without variation in the outcome variable.

#### 6.2.2. *Control for Local COVID-19 Infections*

COVID-19 infections may affect both telemedicine and prescription errors. For instance, the COVID-19 situation may affect patients' and providers' use of telemedicine because of concerns about person-to-person infections. Besides, COVID-19 severity also relates to the average local health conditions and may complicate prescription decisions for patients. To address this concern, we further control for local COVID-19 infections of the county where a patient is located.

Table 6 summarizes the results from two models, in which we include (1) the number of COVID-19 infections on the same day as the encounter (denoted by $SameDayInfection$) and (2) the average number of COVID-19 infections in the week prior to the encounter (denoted by $PastWeekInfection$), respectively. The coefficients for COVID-19 infections are not statistically significant, confirming that patient and provider selections related to COVID-19 have little effect on the UTI sample. Parameter estimates for telemedicine are not significantly different from each other or from the estimate in the main analysis, implying that our results are not driven by regional COVID-19 situations.

**Table 6 Results from the IV Regression (Control for Local COVID-19 Infections)**

| Variable | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.445***$ | 0.137 | $-0.452***$ | 0.138 |
| Same-Day Infection | $-0.063*$ | 0.034 | | |
| Past-Week Infection | | | $-0.005$ | 0.052 |
| Patient Characteristics | Included | | | |
| Provider Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression, with additional control for COVID-19 infections of the county where a patient locates. We re-scale the number of infections by a factor of 1,000 for better representation of the estimates. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, COVID-19 infections, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

#### 6.2.3. *Control for Unobserved Patient Local Factors*

In the main analysis, we explain that the proposed IV is likely valid for two reasons. First, a focal patient's use of telemedicine may correlate with neighboring adoption (i.e., the IV) due to peer influence, similar provider service, and IT infrastructure. Second, neighboring adoptions should not directly affect a provider's prescription decisions for an individual visit, especially considering that we construct the IV using data prior to a focal patient's visit. Nonetheless, unobserved macro factors could be present, such as patients within the same neighborhood being more affluent, more educated, or having access to high-quality doctors. These macro factors may correlate with the IV and directly influence prescription errors.

To address such concern, we impose patient zip code fixed effects, $ZipCode$, in addition to provider fixed effects. The rationale is that the patient zip code fixed effects can account for unobserved patient-level macro factors, including patients' average wealth and education level, as well as access to providers of varying quality across different regions. The result is shown in Model 1 of Table 7. The treatment effect from the second-stage estimation remains robust, both qualitatively and quantitatively similar to our main results.

Another related concern is that the dynamic supply of providers might differ by location and time. For instance, new provider appointments typically occur in the third quarter each year after the residency training ends. If new providers in certain areas receive better training (e.g., less likelihood of prescription errors) and are more tech-savvy (e.g., more likely to use telemedicine), our estimate can be biased. To address such concerns related to unobserved location heterogeneity over time, we impose additional controls, namely $ZipCode \times Quarter$ fixed effects. The results are shown in Model 2 of Table 7, with the second-stage estimation results remaining robust.

**Table 7 Results from the IV Regression (Control for Unobserved Patient Local Factors)**

| Variable | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.413***$ | 0.125 | $-0.478***$ | 0.139 |
| Zip Code Fixed Effects | Yes | | Yes | |
| Zip Code $\times$ Quarter Fixed Effects | No | | Yes | |
| Patient Characteristics | Included | | Included | |
| Provider Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression, with additional controls for patient location fixed effects in model 1, and time-varying location-heterogeneity in model 2. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, and provider fixed effects. Robust standard errors are clustered by provider.

#### 6.2.4. *Alternative Seasonality Controls*

In the main analysis, we have included year-month fixed effects. Given that the data are arranged at the encounter level and that patient or provider behaviors could depend on the day of the week, we further include day-of-week fixed effects. Model 1 of Table 8 reports the results. We can see that the coefficient estimate is similar to the main analysis. In addition, our results are robust to more granular time fixed effects—a combination of day-of-week and year-week fixed effects—as shown in Model 2 of Table 8.

**Table 8 Results from the IV Regression (Control for Alternative Seasonality)**

| Variable | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.452***$ | 0.136 | $-0.466***$ | 0.141 |
| Day of Week Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | | |
| Year-week Fixed Effects | | | Included | |
| Patient Characteristics | Included | | Included | |
| Provider Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression with alternative seasonality controls. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, provider fixed effects, and different combinations of time fixed effects. Robust standard errors are clustered by provider.

Another concern is that the main findings could be driven by some unobserved shocks of certain periods (e.g., lockdowns due to COVID-19). To check if our findings are subject to this concern, we iteratively replicate the IV analysis by omitting one month in each estimation. Table 9 summarizes the results from this leave-month-out analysis. The treatment estimate remains similar both qualitatively and quantitatively, which implies that our results are unlikely driven by time-varying unobserved seasonality.

**Table 9 Leave-Month-Out Analysis**

| Omitted Month | Coefficient | Standard Error | Number of Observations |
|---|---|---|---|
| **Year 2020** | | | |
| January | $-0.445**$ | 0.141 | 15,278 |
| February | $-0.457***$ | 0.154 | 15,296 |
| March | $-0.472***$ | 0.159 | 15,281 |
| April | $-0.473***$ | 0.140 | 15,334 |
| May | $-0.462***$ | 0.131 | 15,338 |
| June | $-0.445***$ | 0.142 | 15,259 |
| July | $-0.476***$ | 0.146 | 15,267 |
| August | $-0.537***$ | 0.138 | 15,258 |
| September | $-0.412***$ | 0.138 | 15,244 |
| October | $-0.441***$ | 0.138 | 15,271 |
| November | $-0.432***$ | 0.131 | 15,313 |
| December | $-0.443***$ | 0.132 | 15,319 |
| **Year 2021** | | | |
| January | $-0.474**$ | 0.131 | 15,355 |
| February | $-0.433***$ | 0.138 | 15,335 |
| March | $-0.440***$ | 0.138 | 15,201 |
| April | $-0.463***$ | 0.134 | 15,243 |
| May | $-0.464***$ | 0.137 | 15,299 |
| June | $-0.446***$ | 0.138 | 15,243 |
| July | $-0.445***$ | 0.136 | 15,226 |
| August | $-0.471***$ | 0.138 | 15,243 |
| September | $-0.418***$ | 0.142 | 15,323 |
| Patient Characteristics | | Included | |
| Provider Fixed Effects | | Included | |
| Year-month Fixed Effects | | Included | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the IV results, with each sample omitting one month from the analysis. The dependent variable is a binary indicator for prescription error. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

#### 6.2.5. *Alternative Definition of Prescription Errors*

In the main analysis, we consider an encounter as having a prescription error if one or more diagnoses have inappropriate prescriptions of antibiotics relative to the guideline suggestions. In this robustness check, we use an alternative definition of prescription errors. More specifically, we denote by $Prescription_{ij}$ a dummy, which is equal to 1 if encounter $i$ has diagnosis $j$ that (1) requires antibiotics but the provider does not prescribe antibiotics or (2) does not require antibiotics but the provider prescribes antibiotics, and 0 otherwise. The fraction of inappropriate prescriptions is $\sum_j^J Prescription_{ij}/J$, where $J$ denotes the number of diagnoses in encounter $i$.

Table 10 summarizes the results for the scenario in which we consider an encounter as having a prescription error if the fraction of inappropriate prescriptions is equal to or greater than 0.5. That is, $PrescripionError_i = 1$ if $\sum_j^J Prescription_{ij}/J \geq 0.5$, and $PrescripionError_i = 0$ if $\sum_j^J Prescription_{ij}/J < 0.5$. We see the coefficient is negative and significantly different from zero at the 1% significance level. The estimate in Table 10 is not significantly different from the estimate in Table 3, which suggests that our results are robust to alternative definitions of prescription errors.

**Table 10 Results from the IV Regression (Alternative Definition of Prescription Error)**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Telemedicine | $-0.433***$ | 0.141 |
| Patient Characteristics | Included | |
| Provider Fixed Effects | Included | |
| Year-month Fixed Effects | Included | |
| Number of Observations | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is prescription error (with an alternative definition). Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

## 7. Heterogeneous Effects

In this section, we explore evidence of heterogeneous effects corresponding to Hypothesis 2 and Hypothesis 3. We conduct the heterogeneity analysis by including the full interaction terms of $Telemedicine$ and our variables of interest, and the results are reported in Table 11.

**Table 11 Heterogeneous Effects**

| Variable | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.252**$ | 0.115 | $-0.505***$ | 0.104 |
| Telemedicine×High Patient Volume | $-0.341***$ | 0.124 | | |
| Telemedicine×Established Patient | | | $0.199**$ | 0.084 |
| Patient Characteristics | Included | | Included | |
| Provider Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the heterogeneous effects by patients' and providers' characteristics. The dependent variable is a binary indicator for prescription error. The key independent variables are telemedicine and the interaction terms of telemedicine with our variables of interests. *High Patient Volume* is a binary indicator of whether a provider's past year UTI patient volume is above the median, and *Established Patient* is a binary indicator of whether a patient has seen a provider for UTI treatment within three years prior to the current visit. We also include the complete list of patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

From the provider side, we measure providers' patient volume using the periodic volume of UTI patients one year before our sample period. We then construct a binary measure $HighPatientVolume$, which equals one if a provider's UTI patient volume is above the median. From model 1, we observe that the treatment effect is greater for providers who practice at a larger scale than those at a smaller scale (Telemedicine×High Patient Volume = $-0.341$, $p < 0.01$). As discussed earlier, providers who are used to seeing high-volume UTI patients may be able to reap the benefits of telemedicine despite limited sensory and tactile information in a virtual setting, because they benefit from economy of scale and are less affected by communication and technical frictions via the virtual channel. This result lends support to Hypothesis 2.

In model 2, we investigate whether an established patient-provider relationship moderates the treatment effect. The results suggest telemedicine has a smaller effect on established patients (Telemedicine×Established Patient = 0.199, $p < 0.05$). As discussed earlier, providers are more familiar with established patients. Comparatively, providers lack prior information about new patients. Therefore, the additional information provided by established patients is less informative than that provided by new patients, and the marginal benefit of telemedicine to established patients is smaller than that to new patients. This result provides support for Hypothesis 3. It also corroborates the first mechanism suggested in Hypothesis 1, which states that telemedicine helps facilitate providers' access to medication information, and thus providers can make better prescription decisions via telemedicine than the offline channel.

## 8. Error Types and Health Outcomes

In this section, we first explore the overall errors by decomposing them into type I and type II prescription errors to gain further insights. We then examine whether telemedicine has any effect on patient health outcomes.

### 8.1. Type I and Type II Errors

We disentangle the overall prescription errors into two categories, as described in Figure 1: (1) prescribing when not recommended by guidelines (type I errors) and (2) not prescribing when recommended (type II errors).

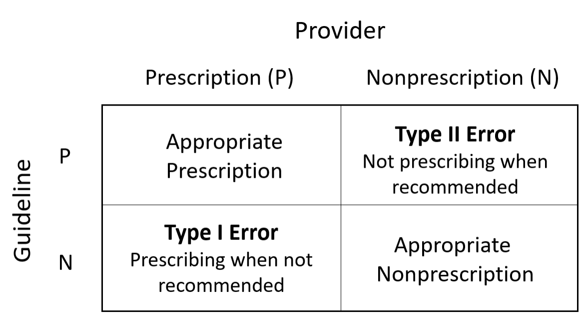


**Figure 1** **Illustration of Type I and Type II Errors**

Table 12 summarizes the results from two separate IV regressions with binary indicators for type I and type II errors as the dependent variables. From the left side of the table, we see the coefficient of $Telemedicine$ is negative and significantly different from zero at the 1% significance level, which suggests that telemedicine reduces the likelihood of type I errors. From the right side of the table, we see the coefficient estimate of $Telemedicine$ is small and insignificant, which suggests telemedicine does not affect the likelihood of type II errors. In other words, the main finding of the reduction in the likelihood of overall prescription error is driven by the reduction in type I errors.

**Table 12 Results from the IV Regression (Type I and Type II Errors)**

| Variable | Type I Errors | | Type II Errors | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.447***$ | 0.121 | $-0.006$ | 0.046 |
| Patient Characteristics | Included | | Included | |
| Provider Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variables are binary indicators for type I and type II errors. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

One potential explanation in the asymmetry between type I and II errors is the differing consequences. Despite serious long-term public health implications related to antibiotic resistance, an individual provider bears little legal or financial consequences for prescribing antibiotics when not recommended (type I errors). This minimal consequence for error may leave room for differing prescription errors across encounter settings. By contrast, not prescribing when recommended by guidelines (type II errors) has imminent legal and financial consequences. An untreated UTI can have serious health consequences such as kidney damage or life-threatening sepsis.[17] These outcomes can trigger malpractice lawsuits regardless of whether a patient is seen virtually or in person, which may explain the trivial difference in type II errors across care delivery settings.

### 8.2. Health Outcomes

Our findings in section 8.1 suggest that telemedicine reduces the likelihood of type I errors without affecting type II errors for UTI patients. This observation leads to a natural follow-up question—how does telemedicine affect patient health outcomes? On the one hand, the reduction in type I errors clearly diminishes the long-term risk of antibiotic resistance, which the IDSA refers to as "collateral damage," describing ecological adverse effects of antibiotic therapy that results in

[17] https://www.mayoclinic.org/diseases-conditions/urinary-tract-infection/symptoms-causes/syc-20353447

the development of drug-resistant organisms and infection with multi-drug-resistant organisms. As Sebesta et al. (2020) note, "*The small increases in collateral damage over so many exposures magnify the impact.*" In other words, although drug resistance is an important public health concern that manifests in the long run, its effect on patient health outcomes is likely minimal in the short run. On the other hand, the reduction in necessary antibiotic prescriptions can put patients at risk of undertreatment, and we may observe changes in the UTI-related complications such as pyelonephritis or urosepsis shortly after prescriptions[18] in our data.

To empirically examine the clinical effects of telemedicine, we track patients' subsequent visits and generate 7- and 30-day revisit indicators that equal 1 if a patient revisited the hospital for UTI-related complications (e.g., pyelonephritis or urosepsis), and 0 otherwise. Table 13 summarizes the results. We see the coefficient of $Telemedicine$ is small and insignificant, which indicates that telemedicine does not increase UTI-related complications in the short term. The finding implies that the reduction in the likelihood of antibiotic prescription errors does not come at the sacrifice of worse health outcomes in the short run. The result is also in line with the lack of significance in the relationship between type II prescription errors and telemedicine, though it may also be due to the rare occurrence of complications.

**Table 13 Results from the IV Regression (Health Outcomes)**

| Variable | 7-Day Complication | | 30-Day Complication | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Telemedicine | $-0.003$ | 0.003 | 0.004 | 0.005 |
| Patient Characteristics | Included | | Included | |
| Provider Fixed Effects | Included | | Included | |
| Year-month Fixed Effects | Included | | Included | |
| Number of Observations | 16,074 | | 16,074 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variables are binary indicators for 7-day and 30-day UTI complication. Independent variables are telemedicine, patient characteristics, provider fixed effects, and time fixed effects. Robust standard errors are clustered by provider.

## 9. Conclusion

Until the COVID-19 crisis, regulatory, financial, and cultural barriers were preventing telemedicine from living up to its potential to increase access to healthcare. The COVID-19 pandemic brought down many of these barriers at once, thus introducing new questions for the academics and the industry that had been exploring the factors contributing to adoption and ways to spur adoption.

[18] https://www.mayoclinic.org/diseases-conditions/urinary-tract-infection/symptoms-causes/syc-20353447

In this paper, we study the following questions: How does telemedicine affect prescription errors, and what does telemedicine mean for patient outcomes?

We examine the case of antibiotic prescription errors for UTIs by considering two types of prescription error: prescribing when not recommended by guidelines (type I errors) and not prescribing when recommended (type II errors). Using OLS regression, we find a significant reduction (20.7%) in the likelihood of overall prescription errors (type I and II errors combined) when the clinical setting is virtual as opposed to in-person. To address endogeneity issues related to the adoption of telemedicine, we employ various fixed effects as well as an IV approach that reveals an even greater reduction (45.3%). Our results are consistent through a battery of robustness checks.

The effect of telemedicine is not uniform across providers and patients. We find that providers with high patient volume (i.e., have more experience in treating UTIs) have a larger reduction in prescription errors via telemedicine. On the patient side, patients who have an established relationship with their provider experience a smaller reduction in antibiotic prescription errors. These results provide valuable insights for the insurance industry and policymakers, as they need to consider prescription errors in their efforts to expand telemedicine use among particular segments of patients and providers.

We further investigate prescription errors by disentangling type I from II errors and show that the reduction in errors is mainly driven by a reduction in type I errors as opposed to type II errors. This finding leads to further health implications. First, type II errors may leave UTIs untreated, causing potentially serious complications. Our finding of only minimal change in type II errors implies little effect on such complications. We also directly check patient health outcomes such as kidney infection and sepsis and find no statistical difference between virtual and in-person encounters. Second, type I errors have potential health implications related to antibiotic overprescription. Antibiotic overprescription is a major public health concern, and its impact may be measured by infections with drug-resistant microorganisms in the long run. Future research could examine the effect of telemedicine use on long-term health outcomes with long-panel patient-encounter data.

One concern in interpreting our results is that the introduction of the telehealth system may be accompanied by upgrades in other health IT systems (such as EHR or HIE). If this is the case, providers might be able to access better information via the upgraded system. The reduction in prescription errors could then be due to those confounding IT infrastructural changes. Note that we include provider fixed effects throughout our analyses, which already factors in time-invariant IT capabilities at the provider level. Conversations with providers in several healthcare institutions that adopted telehealth revealed that during telemedicine consultations, they could access the same patients' information as in-person settings. Although this evidence significantly alleviates our concern, we cannot completely rule out the possibility that the improved prescription decisions might come from time-varying confounding IT adoptions, unless detailed information on the telemedicine interface and IT adoptions for each provider become available to researchers.

Our findings have several broader implications for a variety of stakeholders. First, for patients who are hesitant to try telemedicine, our results demonstrate a major potential benefit—a lower likelihood of prescription errors. In our data, we also show that the likelihood of revisits due to severe complications is not statistically different for telemedicine and in-person care settings. Given that more accurate prescribing can contribute to a potential reduction in drug resistance in the long run, our results can provide useful information to patients who are contemplating the use of telemedicine. Second, our results imply that providers and hospital managers should consider prescription errors as a performance metric in deploying telemedicine. This is because reducing prescription errors can benefit patient outcomes while reducing drug costs by stemming unnecessary prescriptions. Our findings are also relevant to insurers because such cost savings can improve their bottom line as well. Third, our findings also point to public policy implications. With antibiotic overprescription being a major public health concern, our findings suggest an additional benefit of telemedicine when the federal and state governments consider policy changes to spur further expansion of virtual clinical settings. We also show that prescription changes via telemedicine visits do not lead to negative patient outcomes related to type II errors and associated undertreatment. Therefore, policy makers may safely extend temporary incentives for telemedicine beyond the pandemic. Although the effect of telemedicine on prescription errors may apply primarily to non-COVID-19 related conditions, policy makers need to continue monitoring the use of telemedicine, the number of prescription errors for different medical conditions and drugs, and corresponding patient outcomes as well as costs to decide whether to further incentivize telemedicine use.

## References


Agarwal R, Gao G, DesRoches C, Jha AK (2010) Research Commentary— The digital transformation of healthcare: Current status and the road ahead. *Information Systems Research* 21(4):796–809.

Ailes EC, Summers AD, Tran EL, Gilboa SM, Arnold KE, Meaney-Delman D, Reefhuis J (2018) Antibiotics dispensed to privately insured pregnant women with urinary tract infections—United States, 2014. *Morbidity and Mortality Weekly Report* 67(1):18.

Alexander GC, Tajanlangit M, Heyward J, Mansour O, Qato DM, Stafford RS (2020) Use and content of primary care office-based vs telemedicine care visits during the COVID-19 pandemic in the US. *JAMA Network Open* 3(10):e2021476–e2021476.

Angrist JD, Pischke JS (2008) *Mostly Harmless Econometrics* (Princeton University Press).

Asare SK, McDaniel LS (1996) The effects of familiarity with the preparer and task complexity on the effectiveness of the audit review process. *Accounting Review* 139–159.

Ash JS, Berg M, Coiera E (2004) Some unintended consequences of information technology in health care: the nature of patient care information system-related errors. *Journal of the American Medical Informatics Association* 11(2):104–112.

Ayabakan S, Bardhan I, Zheng E (2020) Impact of telehealth use on healthcare utilization: A quasi-experimental study of Maryland patients. Available at SSRN: https://ssrn.com/abstract=3707829 .

Bartel AP, Chan CW, Kim SH (2020) Should hospitals keep their patients longer? The role of inpatient care in reducing postdischarge mortality. *Management Science* 66(6):2326–2346.

Bavafa H, Hitt LM, Terwiesch C (2018) The impact of e-visits on visit frequencies and patient health: Evidence from primary care. *Management Science* 64(12):5461–5480.

Bavafa H, Terwiesch C (2019) Work after work: The impact of new service delivery models on work hours. *Journal of Operations Management* 65(7):636–658.

Berry Jaeker JA, Tucker AL (2017) Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. *Management Science* 63(4):1042–1062.

Bhargava HK, Mishra AN (2014) Electronic medical records and physician productivity: Evidence from panel data analysis. *Management Science* 60(10):2543–2562.

Buntin MB, Burke MF, Hoaglin MC, Blumenthal D (2011) The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs* 30(3):464–471.

Chua KP, Fischer MA, Linder JA (2019) Appropriateness of outpatient antibiotic prescribing among privately insured us patients: ICD-10-CM based cross sectional study. *BMJ* 364.

Clark AW, Durkin MJ, Olsen MA, Keller M, Ma Y, O'Neil CA, Butler AM (2021) Rural–urban differences in antibiotic prescribing for uncomplicated urinary tract infection. *Infection Control & Hospital Epidemiology* 1–8, ISSN 0899-823X, 1559-6834.

Clark JR, Huckman RS (2012) Broadening focus: Spillovers, complementarities, and specialization in the hospital industry. *Management Science* 58(4):708–722.

Cliff S (2014) The July effect is real: New doctors really do make hospitals more dangerous. Retrieved from https://www.vox.com/2014/7/13/5893653/the-july-effect-is-real-new-doctors-really-do-make-hospitals-more.

Delana K, Deo S, Ramdas K, Babu G, Ravilla T (2019) Multichannel delivery in healthcare: The impact of telemedicine centers in Southern India. Working paper, Indian School of Business, India .

DesRoches CM, Campbell EG, Rao SR, Donelan K, Ferris TG, Jha A, Kaushal R, Levy DE, Rosenbaum S, Shields AE, et al. (2008) Electronic health records in ambulatory care—A national survey of physicians. *New England Journal of Medicine* 359(1):50–60.

Dranove D, Forman C, Goldfarb A, Greenstein S (2014) The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy* 6(4):239–70.

Elixhauser A, Steiner C, Harris DR, Coffey RM (1998) Comorbidity measures for use with administrative data. *Medical Care* 8–27.

Field MJ, et al. (1996) *Telemedicine: A Guide to Assessing Telecommunications for Health Care* (National Academies Press).

Ganju KK, Atasoy H, McCullough J, Greenwood B (2020) The role of decision support systems in attenuating racial biases in healthcare delivery. *Management Science* 66(11):5171–5181.

Goh JM, Gao G, Agarwal R (2011) Evolving work routines: Adaptive routinization of information technology in healthcare. *Information Systems Research* 22(3):565–585.

Goldfarb A, Tucker CE (2011) Privacy regulation and online advertising. *Management Science* 57(1):57–71.

Gomez T, Anaya YB, Shih KJ, Tarn DM (2021) A qualitative study of primary care physicians' experiences with telemedicine during COVID-19. *The Journal of the American Board of Family Medicine* 34(Supplement):S61–S70.

Gupta K, Hooton TM, Naber KG, Wullt B, Colgan R, Miller LG, Moran GJ, Nicolle LE, Raz R, Schaeffer AJ, et al. (2011) International clinical practice guidelines for the treatment of acute uncomplicated cystitis and pyelonephritis in women: A 2010 update by the Infectious Diseases Society of America and the European Society for Microbiology and Infectious Diseases. *Clinical Infectious Diseases* 52(5):e103–e120.

Hersh AL, Stenehjem E, Daines W (2019) Re: Antibiotic prescribing during pediatric direct-to-consumer telemedicine visits. *Pediatrics* 144(2).

Huang N, Yan Z, Yin H (2021) Effects of online–offline service integration on e-healthcare providers: A quasi-natural experiment. *Production and Operations Management* .

Hwang EH, Guo X, Tan Y, Dang Y (2021) Delivering healthcare through teleconsultations: Implication on offline healthcare disparity. *Information Systems Research* (Forthcoming).

Kc DS, Scholtes S, Terwiesch C (2020) Empirical research in healthcare operations: past research, present understanding, and future opportunities. *Manufacturing & Service Operations Management* 22(1):73–83.

Kc DS, Terwiesch C (2011) The effects of focus on performance: Evidence from California hospitals. *Management Science* 57(11):1897–1912.

Kruse CS, Karem P, Shifflett K, Vegi L, Ravi K, Brooks M (2018) Evaluating barriers to adopting telemedicine worldwide: A systematic review. *Journal of Telemedicine and Telecare* 24(1):4–12.

Kuntz L, Scholtes S, Sülz S (2019) Separate and concentrate: Accounting for patient complexity in general hospitals. *Management Science* 65(6):2482–2501.

Li Y, Lu LX, Lu SF, Chen J (2021) The value of health information technology interoperability: Evidence from interhospital transfer of heart attack patients. *Manufacturing & Service Operations Management* 0(0).

Lin CCC, Dievler A, Robbins C, Sripipatana A, Quinn M, Nair S (2018) Telehealth in health centers: Key adoption factors, barriers, and opportunities. *Health Affairs* 37(12):1967–1974.

Lu SF, Rui H, Seidmann A (2018) Does technology substitute for nurses? Staffing decisions in nursing homes. *Management Science* 64(4):1842–1859.

McCullough J, Ganju KK, Ellimoottil C (2021) Does telemedicine transcend disparities or create a digital divide? Evidence from the COVID-19 pandemic Working paper, University of Michigan, Ann Arbor .

Mehrotra A, Paone S, Martich GD, Albert SM, Shevchik GJ (2013) A comparison of care at e-visits and physician office visits for sinusitis and urinary tract infection. *JAMA Internal Medicine* 173(1):72–74.

Miller EA (2003) The technical and interpersonal aspects of telemedicine: Effects on doctor–patient communication. *Journal of Telemedicine and Telecare* 9(1):1–7.

Powell RE, Henstenburg JM, Cooper G, Hollander JE, Rising KL (2017) Patient perceptions of telehealth primary care video visits. *The Annals of Family Medicine* 15(3):225–229.

Rajan B, Tezcan T, Seidmann A (2019) Service systems with heterogeneous customers: Investigating the effect of telemedicine on chronic care. *Management Science* 65(3):1236–1267.

Rastogi R, Martinez KA, Gupta N, Rood M, Rothberg MB (2020) Management of urinary tract infections in direct to consumer telemedicine. *Journal of General Internal Medicine* 35(3):643–648.

Ray KN, Shi Z, Gidengil CA, Poon SJ, Uscher-Pines L, Mehrotra A (2019) Antibiotic prescribing during pediatric direct-to-consumer telemedicine visits. *Pediatrics* 143(5).

Rogove HJ, McArthur D, Demaerschalk BM, Vespa PM (2012) Barriers to telemedicine: Survey of current users in acute care units. *Telemedicine and e-Health* 18(1):48–53.

Royce TJ, Sanoff HK, Rewari A (2020) Telemedicine for cancer care in the time of COVID-19. *JAMA Oncology* 6(11):1698–1699.

Saghafian S, Hopp WJ, Iravani SM, Cheng Y, Diermeier D (2018) Workload management in telemedical physician triage and other knowledge-based service systems. *Management Science* 64(11):5180–5197.

Sebesta EM, March A, Sayegh C, Li G, Love M, Badalato GM, Ferdschneider M, Cooper KL (2020) Reducing overprescribing of antibiotics for suspected urinary tract infections in a health sciences campus student health service. *Neurourology and Urodynamics* 39(1):220–224.

Serrano C, Karahanna E (2016) The compensatory interaction between user capabilities and technology capabilities in influencing task performance: An empirical assessment in telemedicine consultations. *MIS Quarterly* 40(3):597–621.

Shi Z, Mehrotra A, Gidengil CA, Poon SJ, Uscher-Pines L, Ray KN (2018) Quality of care for acute respiratory infections during direct-to-consumer telemedicine visits for adults. *Health Affairs* 37(12):2014–2023.

Sun S, Lu SF, Rui H (2020) Does telemedicine reduce emergency room congestion? Evidence from New York State. *Information Systems Research* 31(3):972–986.

Tariq RA, Vashisht R, Sinha A, Scherbak Y (2021) Medication dispensing errors and prevention. *StatPearls* (Treasure Island (FL): StatPearls Publishing), URL `http://www.ncbi.nlm.nih.gov/books/NBK519065/`.

Uscher-Pines L, Malsberger R, Burgette L, Mulcahy A, Mehrotra A (2016) Effect of teledermatology on access to dermatology care among Medicaid enrollees. *JAMA Dermatology* 152(8):905–912.

Wang L, Yan L, Zhou T, Guo X, Heim GR (2020) Understanding physicians' online-offline behavior dynamics: An empirical study. *Information Systems Research* 31(2):537–555.

Weigel G, Ramaswamy A, Sobel L, Salganicoff A, Cubanski J, Freed M (2020) Opportunities and barriers for telemedicine in the US during the COVID-19 emergency and beyond. Kaiser Family Foundation.

Yao P, Clark S, Gogia K, Hafeez B, Hsu H, Greenwald P (2020) Antibiotic prescribing practices: Is there a difference between patients seen by telemedicine versus those seen in-person? *Telemedicine and e-Health* 26(1):105–107.