Does Telemedicine Affect Physician Decisions? Evidence from Antibiotic Prescriptions

TI Kim
Jindal School of Management
University of Texas at Dallas
ti.kim@utdallas.edu

Shujing Sun
Jindal School of Management
University of Texas at Dallas
shujing.sun@utdallas.edu

Guihua Wang
Jindal School of Management
University of Texas at Dallas
guihua.wang@utdallas.edu

Abstract

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. After accounting for potential endogeneity issues using provider fixed effects and an instrumental variable approach, we find a significantly lower likelihood of prescription errors with telemedicine relative to in-person encounters. We also find heterogeneous effects by a provider's patient volume and the patient-provider relationship.

Keywords: antibiotics, COVID-19 research database, health IT, prescription error, telemedicine

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, because 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 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. 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

[1] More details are available at https://www.commonwealthfund.org/publications/2020/apr/impact-covid-19-outpatient-visits.

URI: https://hdl.handle.net/10125/103327
978-0-9981331-6-4

million patients, and cost the economy more than $40 billion (Tariq et al., 2021). 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 assembled urinary tract infection (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. To address potential endogeneity issues, 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.[2] The IV estimate shows a significant reduction in the likelihood of prescription errors (45.3%). 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 prescription errors among providers with higher past UTI-patient volume and new patients who have no prior encounters with providers.

The rest of the paper is organized as follows. We first provide an overview of related literature. We then discuss the clinical setting and describe the data, empirical strategy, and main results. After that, we explore heterogeneous effects 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 telemedicine and prescription errors.

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

[3]More details are available at https://www.aafp.org/news/media-center/kits/telemedicine-and-telehealth.html.

2.2. 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 information technology (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 4.2.

3. Clinical Setting and Data

In this section, we provide details on the clinical setting, data preparation, and summary statistics.

3.1. 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. Finally, 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.[4] Antibiotic prescription errors can increase antibiotic resistance among the 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.[5]

3.2. Data Description and Preparation

We obtain proprietary encounter-level EHR data including diagnosis, procedures, labs, vitals, medications and histories sourced from participating members of the Healthjump network in the U.S.[6] 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.[7]

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.

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., Bartel et al., 2020; Berry Jaeker and Tucker, 2017; Elixhauser et al., 1998). 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.

Finally, 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[8] 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.

[4] More details are available at https://www.cdc.gov/drugresistance/index.html.

[5] More details are available at https://www.wsj.com/articles/SB10001424052702303678404579536284129494564.

[6] The data, technology, and services used in the generation of these research findings were generously supplied pro bono by the COVID-19 Research Database partners, who are acknowledged at https://covid19researchdatabase.org/.

[7] More details are available at https://www.cms.gov/.

[8] 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." More details are available at https://www.aapc.com/blog/37138-how-to-determine-new-vs-established-patient-status/.

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 readmission and complication.

3.3. 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. 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. The lower part of Table 1 summarizes the key independent variables about patient characteristics. Non-pregnant female patients account for the majority of UTI visits. Around one third of patients have at least one comorbidity. Finally, 28.4% of patients have seen a provider for UTI treatment within three years prior to the current visit.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.
Prescription Error	0.668	0.471
Patient Age	45.869	21.168
Patient Female	0.899	0.302
Patient Pregnant	0.015	0.121
Patient with Comorbidity	0.337	0.473
Established Patient	0.284	0.451
Number of Observations	16,074	

Note: This table reports the summary statistics of the data utilized in this study.

4. 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.

4.1. 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, 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.

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 3.2, 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.[9]

In the main analysis, we use a 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.

The relation between the dependent and independent

[9]Using alternative time fixed effects does not change the main conclusion of this study.

variables can be described using equation (1):

$$\begin{aligned} PrescriptionError_i \quad = \quad & \alpha_0 + \alpha_1 Telemedicine_i \\ & + \alpha_2 X_i + \alpha_3 Provider_i \\ & + \alpha_4 Time_i + \epsilon_i, \end{aligned} \tag{1}$$

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 the patient for encounter i, and ϵ_i denotes the error term.

4.2. Identification

Estimating equation (1) using the ordinary least squares (OLS) regression poses challenges to interpreting α_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.[10] 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 likelihood of antibiotic prescription errors for UTI encounters after controlling for these covariates.

We use two-stage least squares regression 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,

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

where ξ_i denotes the error term. The coefficient β_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

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

where ζ_i denotes the error term. We are particularly interested in the coefficient γ_1. A positive coefficient would suggest that telemedicine increases the likelihood of prescription errors, whereas a negative coefficient would suggest the opposite. Comparing α_1 in equation (1) and γ_1 in equation (3) allows us to better understand the direction of the potential bias due to endogeneity issues.

[10] 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.

5. Results

In this section, we first show the results from our main analysis. We then show the results from the heterogeneity analysis.

5.1. 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. 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
Neighbor Telemedicine	0.648***
	(0.065)
Patient Characteristics	Included
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. A coefficient of -0.453 suggests that the use of telemedicine reduces the likelihood of prescription errors by 45.3%. 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.

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. 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 3. Results from the IV Regression

Variable	Coefficient
Telemedicine	-0.453***
	(0.136)
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 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.

Table 4. Results from the OLS Regression

Variable	Coefficient
Telemedicine	-0.207***
	(0.021)
Patient Characteristics	Included
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.

5.2. Heterogeneous Effects

In this section, we explore evidence of heterogeneous effects. 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 5.

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 ($Telemedicine \times HighPatientVolume = -0.341$, $p < 0.01$). 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.

Table 5. Heterogeneous Effects

Variable	Model 1	Model 2
Telemedicine	-0.252**	-0.505***
	(0.115)	(0.104)
Telemedicine×HighPatientVolume	-0.341***	
	(0.124)	
Telemedicine×EstablishedPatient		0.199**
		(0.084)
Patient Characteristics	Included	
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 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. $HighPatientVolume$ is a binary indicator of whether a provider's past year UTI patient volume is above the median, and $EstablishedPatient$ 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.

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 ($Telemedicine \times EstablishedPatient = 0.199$, $p < 0.05$). 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 suggests that telemedicine helps facilitate providers' access to medication information, and thus providers can make better prescription decisions via telemedicine than the offline channel.

6. Discussion and 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. In this paper, we study the following questions: How does telemedicine affect prescription errors?

Using the case of antibiotic prescription errors for UTIs and an OLS regression, we find a significant reduction (20.7%) in the likelihood of prescription errors 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%).

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.

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). 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. 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. Therefore, policy makers may safely extend temporary incentives for telemedicine beyond the pandemic.

Finally, 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

Ailes, E. C., Summers, A. D., Tran, E. L., Gilboa, S. M., Arnold, K. E., 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, G. C., Tajanlangit, M., Heyward, J., Mansour, O., Qato, D. M., & Stafford, R. S. (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, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics*. Princeton University Press.

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, A. P., Chan, C. W., & Kim, S.-H. (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, L. M., & 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, J. A., & Tucker, A. L. (2017). Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. *Management Science*, *63*(4), 1042–1062.

Chua, K.-P., Fischer, M. A., & Linder, J. A. (2019). Appropriateness of outpatient antibiotic prescribing among privately insured us patients: ICD-10-CM based cross sectional study. *BMJ*, *364*.

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.

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, D. R., & Coffey, R. M. (1998). Comorbidity measures for use with administrative data. *Medical Care*, 8–27.

Field, M. J. et al. (1996). *Telemedicine: A guide to assessing telecommunications for health care*. National Academies Press.

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

Gupta, K., Hooton, T. M., Naber, K. G., Wullt, B., Colgan, R., Miller, L. G., Moran, G. J., Nicolle, L. E., Raz, R., Schaeffer, A. J., 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, A. L., Stenehjem, E., & Daines, W. (2019). Re: Antibiotic prescribing during pediatric direct-to-consumer telemedicine visits. *Pediatrics*, *144*(2).

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

Kruse, C. S., 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.

Lin, C.-C. C., 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, S. F., Rui, H., & Seidmann, A. (2018). Does technology substitute for nurses? Staffing decisions in nursing homes. *Management Science*, *64*(4), 1842–1859.

McCullough, J., Ganju, K. K., & 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, G. D., Albert, S. M., & Shevchik, G. J. (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.

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, K. A., Gupta, N., Rood, M., & Rothberg, M. B. (2020). Management of urinary tract infections in direct to consumer telemedicine. *Journal of General Internal Medicine*, *35*(3), 643–648.

Ray, K. N., Shi, Z., Gidengil, C. A., Poon, S. J., Uscher-Pines, L., & Mehrotra, A. (2019). Antibiotic prescribing during pediatric direct-to-consumer telemedicine visits. *Pediatrics*, *143*(5).

Rogove, H. J., McArthur, D., Demaerschalk, B. M., & Vespa, P. M. (2012). Barriers to telemedicine: Survey of current users in acute care units. *Telemedicine and e-Health*, *18*(1), 48–53.

Royce, T. J., Sanoff, H. K., & Rewari, A. (2020). Telemedicine for cancer care in the time of COVID-19. *JAMA Oncology*, *6*(11), 1698–1699.

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

Shi, Z., Mehrotra, A., Gidengil, C. A., Poon, S. J., Uscher-Pines, L., & Ray, K. N. (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, S. F., & Rui, H. (2020). Does telemedicine reduce emergency room congestion? Evidence from New York State. *Information Systems Research*, *31*(3), 972–986.

Tariq, R. A., Vashisht, R., Sinha, A., & Scherbak, Y. (2021). Medication dispensing errors and prevention. *StatPearls*. StatPearls Publishing. Retrieved July 4, 2021, from 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.

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.