The Future of Remote Medicine: Preliminary Evidence from Primary Care Use During and After the COVID-19 Lockdown

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PRELIMINARY: WORK IN PROGRESS

December 20, 2020

Abstract

COVID-19 has precipitated a major shift to remote healthcare delivery, which raises both concerns about diagnostic quality and hopes for improved access and new hybrid care models. Using data on millions of visits from a large HMO in Israel, we document this shift and uses it to study the impact of remote medicine on physician decisions and patient outcomes.

We account for the endogeneity of visit setting using two complementary strategies. First, we use within-clinic variation in physician tendency to shift care remotely during the first COVID-19 lockdown as a proxy for patient access to remote medicine in later periods. Using a difference-in-difference specification, we then compare visit outcomes of high- and low-access patients, between 2019 (the pre-COVID baseline) and the post-lockdown period that was characterized by a partial (and temporary) return to normalcy. The second strategy compares, for specific common conditions, visit outcomes between matched in-person and remote visits of the *same* physician.

Preliminary analysis of Urinary Tract Infection (UTI) and differential diagnoses shows that post lockdown, remote and in-person visits resulted in *similar* rates of diagnoses, prescriptions, and subsequent healthcare utilization. These preliminary results suggest that using primary care remotely may not compromise quality, although they do not account for heterogeneity across patients, and results may be different for conditions for which physical examination is more essential. Broadly, results will inform the policy discussion about the role of remote medicine in the post-pandemic era.

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Introduction

Background and Motivation

The COVID-19 pandemic has precipitated a rapid expansion in the use of remote medicine services, which provide the opportunity to use medical care while mitigating the the spread of COVID-19 contagion. Since March 2020, many healthcare systems throughout the world substantially expanded the provision and coverage of remote medicine, leading to a surge in both supply and demand for it (Alexander et al., 2020; Mehrotra et al., 2020b; Patel et al., 2020). For example, in the United States, remote visits accounted for less than 1 percent of primary-care visits before 2020. In March 2020, this share rose sharply as a result of COVID-19, peaking at nearly 20 percent in April, before stabilizing at much higher levels than before the pandemic (Mehrotra et al., 2020a; Patel et al., 2020). Beyond the obvious value of remote medicine for maintaining access to care while mitigating contagion during the pandemic, these unprecedented and rapid changes raise the question of what will become of these new approaches to treatment once the COVID-19 threat has passed (Dorsey and Topol, 2020). Yet evidence from before the pandemic is limited, because pre-2020, remote medicine covered smaller and different set of services.

Providing care remotely entails both risks and opportunities. Remote medicine has the potential to improve access to care for immobile and rural populations (thus reducing inequality), to reduce the risk of contagion for infectious diseases other than COVID-19, and to revolutionize primary care by expediting and lowering the cost of triage, allowing providers to resolve cases remotely while eliminating the travel and hassle cost of going to clinics (Hollander and Carr, 2020). It may increase the allocative efficiency by expanding the geographic reach of specialized providers. It also reduces the (travel, time, and contagion) costs of followup encounters and may make it easier for patients to schedule with their own primary care providers, supporting continuity of care.

Remote medicine also raises concerns. One is that widespread access to remote medicine might increase spending on low-value care. The difficulty of remotely diagnosing conditions for which physical examination is part of the protocol, coupled with the ease-of-access that might increase the tendency of patients to seek care for conditions that might have resolved spontaneously, could increase costs and result in overuse of diagnostic services, follow-up in-person primary care, or specialist services (Ashwood et al., 2017). A separate concern is that differential adoption, mediated by education and socioeconomic status, could make remote medicine yet another contributor to increasing inequality in healthcare access (Nicola et al., 2020; Cutter et al., 2020). However, given the minimal use of remote medicine before COVID-19, there is limited current evidence that would allow an empirical assessment of the quantitative importance of each of these issues.

Contribution

Analyzing the shift in 2020 to remote medicine using administrative data from the largest HMO in Israel, we provide quantitative evidence on the nature and impact of the shift to remote medicine, and on its effects on care outcome. Specifically, we document the characteristics of providers, patients, and cases that were more likely to use remote medicine in 2020. We then evaluate the impact of providing care remotely (as opposed to in-person) on the demand for care on the one hand, and on diagnostic quality, visit resolution, and subsequent outcomes on the other hand. Such evidence are of direct relevance to policy and are important for guiding decisions regarding the future organization of healthcare services.

Empirical Strategy

Our aim is to evaluate the impact of shifting care remotely on physicians' diagnostic accuracy, treatment decisions, and patient outcomes. Our analysis shows that a lot of heterogeneity existed in the share of cases physicians (and patients) have moved remotely, providing a useful source variation. However, there are several identification challenges. First, the number and composition of cases may be endogenous to the ease-of-access to remote medicine, which reduces patient travel and time costs and may make patients seek more care and at earlier stages. Second, the visit setting is endogenous, as physicians and patients using remote medicine may not be the same as those visiting clinics in person. Third, diagnosis accuracy may depend on the setting, especially for conditions that require physical examination, hence the nature of the setting may impact the observed diagnosis.

To account for these sources of endogeneity, we use two complementary approaches. The first approach identifies the impact of remote medicine on outcomes, using the variation in access to remote medicine brought by the sharp—and highly heterogeneous—switch to remote medicine during the first (March-April 2020) COVID-19 lockdown. We use variation within local clinics in the tendency of individual physicians to shift to remote medicine during the lockdown period as a proxy for the access their regular patients have to remote visits in subsequent periods. Based on this proxy, we compare, using a difference-in-differences framework, both the tendency to use care and the visit outcomes conditional on doing so, between patients with high versus low access to remote medicine, between the 2019 baseline and the post-lockdown period of May–June 2020, during which Israel had very low numbers of COVID-19 cases and which was characterized by a partial and temporary return to normalcy.

The second strategy complements the breadth of the first strategy by using a more granular analysis of physician decisions. It compares diagnoses, treatments, and outcomes between remote in-person visits within physician, among similar patients, for a more homogeneous set of conditions. We exploit the fact that, post-lockdown, many physicians saw patients both in person and remotely. This allows us to compare, for common conditions, visit outcomes between

patients of the *same* physician, which accounts for between-physician heterogeneity in practice style. To account for potential selection into (remote or in-person) setting among patients, we match remote patients with similar in-person patients seen by the same physician. Finally, to account for diagnosis heterogeneity, we compare visit outcomes within more homogeneous conditions defined by differential diagnoses—sets of possible conditions that have a common set of symptoms.

Data

Data Source. Our data come from Clalit Health Services, the largest of Israel's four non-profit health maintenance organizations (HMOs) that provide universal, mandatory tax-funded healthcare coverage from birth onward to all Israeli residents. Coverage broadly resembles that of Medicare parts A, B, and D and includes hospital admissions, outpatient services, physician consults, drugs, and durable medical equipment. Clalit is an integrated provider and insurer, providing most of the services it finances by salaried providers and reimbursing services purchased from external providers. It covers over one-half of the Israeli population, approximately 4.5 million enrollees of all ages. Annual switching rate is very low, resulting in a very stable population of enrollees.

Clalit data are particularly well suited for analyzing remote medicine. Clalit maintains detailed and comprehensive claim-level data associated with all the services it provides or reimburses to its universe of enrollees. In addition, Clalit also has rich data from electronic medical records (EMR) that cover nearly all office-based (and remote) encounters and a large share of all hospital admissions. Such data allow a granular analysis of physician decisions and care outcomes.

Remote medicine in Clalit. In years prior to the COVID-19 outbreak, Clalit has been gradually expanding its remote medicine capabilities, with patient portals allowing prescription refills and other asynchronous requests, but the scope and utilization of synchronous remote medicine were limited mainly to after-hour virtual clinics and physicians following up on lab test results. Primary care was provided predominantly in person. Since March 2020, patients have been allowed—indeed, encouraged—to schedule remote visits with their primary care physicians and other providers. These visits use either phone or non-secure video conferencing technology (which we currently refer to collectively as "remote visits," though we may later separate video from phone; patients can also purchase a remote sensor for taking bio-measures, but adoption of this option is still limited). Physicians would continue to see patients in person in Clalit clinics throughout the lockdown period, but school closures, limited public transit, and the risk of COVID-19 contagion increased the tendency of both providers and patients to use remote medicine, which, as our preliminary analysis below shows, sharply increased during this period.

Study Period. We plan to focus on the period between January 2019 and the most recent data year available at the time of the analysis (2021). Our design exploits variations in access to in-person and remote medicine brought by the COVID-19 outbreak.

We split our sample into three sub-periods: before ("baseline", or "pre" period), during ("peak" period), and after ("post" period) the first COVID-19 lockdown. The pre–COVID-19 period is used to establish the baseline pre-pandemic medical practice, which was predominantly in person. This first lockdown involved stay-at-home orders and mandatory and tightly enforced mobility restrictions that, as our preliminary analysis shows, resulted in a massive increase in the use of remote medicine. This lockdown resulted in a sharp decline in COVID-19 cases and a low COVID-19 positivity rate in tests and was followed by a rapid (and, in retrospect, temporary) return to normalcy. During this "post" period of May–June 2020, lockdown restrictions were rapidly relaxed, including school, transit, restaurant, and mall opening (with mandatory masks, social distancing, and limitations on crowd size). Our comparison of remote and in-person visits focuses on this period. We censor the "post" period in July, when COVID-19 incidence started to increase again, leading up to a second wave and another lockdown in September.

Main Variables. Our main "treatment" variable is the visit setting: *in-person* visits (in clinics) or *remote* consults (via phone or video conferencing). We consider the effect of visit setting on visit outcomes. For each visit, we observe a free-text visit summary which includes reported symptoms, coded diagnoses, lab referrals, and referrals to other providers.[1] We also observe follow-up healthcare utilization and cost (for all types of services).

For each patient, we observe exceptionally rich medical records that include their demographic information, zip-based socioeconomic status score, complete history and subsequent use of healthcare utilization, all coded diagnoses, a list of chronic conditions (if any), risk scores from Johns Hopkins Adjusted Clinical Groups (ACG; a commercial classifier), and EMR measurements that include vital sign measurements (such as systolic blood pressure and BMI), and lab test results (such as cholesterol or glomerular filtration rate levels).

Empirical Specifications

This first, difference-in-difference strategy, involves two steps. First, we estimate, using data from the lockdown period, each physician's tendency to work remotely, adjusting for case mix:

$$\textit{Remote}_{ijtl} = \delta_1 X_{it} + \mu_t + \eta_l + \phi_j + \varepsilon_{ijtl}, \tag{1}$$

[1] Referrals and prescriptions are all digitized for both in-person and remote visits. Regardless of the setting of the index visits, patients perform lab tests and fill prescriptions in-person, using the same network of testing facilities and pharmacies.

where $ijtl$ are indices for the index visit of patient i with physician j at time t and location (clinic) l; $\textit{Remote}_{ijtl}$ is an indicator for a remote (rather than in-person) visit; X_{it} denote visit controls, including patient age, gender, chronic conditions, ACG score, diagnosis category, and EMR-sourced past measures of health status; and μ_t and η_l are week and location fixed effects. The estimated physician dummies from this regression, $\hat{\phi}_j$, is our measure of the tendency of each physician to shift to remote medicine during the lockdown period.

We then estimate the following difference-in-differences model, using the sample of visits in the three sub-periods: baseline, the lockdown, and post-lockdown:

$$\begin{aligned}\textit{Outcome}_{i_{(j)}tl} =& \alpha_1 \widehat{\textit{RemoteCareAccess}}_j + \\ & \beta_1 \widehat{\textit{RemoteCareAccess}}_j \times \textit{Lockdown}_t + \gamma_1 \textit{Lockdown}_t \\ & \beta_2 \widehat{\textit{RemoteCareAccess}}_j \times \textit{PostLockdown}_t + \gamma_2 \textit{PostLockdown}_t + \\ & \delta_2 X_{i_{(j)}tl} + \mu_t + \eta_l + \varepsilon_{i_{(j)}tl} \end{aligned} \tag{2}$$

Where $\widehat{\textit{RemoteCareAccess}}$ is one if $\hat{\phi}_j$ is above the median among physicians in our sample and zero otherwise, and *Outcome* is one of our outcome measures. The index $i_{(j)}$ denotes the set of patients whose main primary care physician is j. Note that, in order to overcome possible selection related to the difference in availability between early adopters of remote medicine and other physicians, we consider how a physician's adoption affects the outcomes of post-lockdown visits of *all* their patients, regardless of whether these patients visited the main primary physician or other physicians.

The main parameter of interest is β_2: the effect of remote medicine access on visit probability on the one hand, and on visit outcomes on the other hand. Note that because we include clinic fixed effects, the identifying variation comes from comparing patients who are served by doctors in the same local clinic, who varied in their rate of adoption of remote medicine. The identification assumption is that the patients whose main providers are high and low adopters of remote medicine have similar trends in morbidity, and therefore in visit outcomes. Identification does not require that physicians randomly select into online use. Indeed, they may not. It only requires that without the shift to remote medicine, the morbidity of the panels of different physicians would have exhibited parallel trends. Since we observe the entire panel of each physician, we can evaluate evidence in support of this assumption, by examining pre-trends in visit outcomes, using a version of the model in equation (2) with flexible leads and lags.

The second strategy will compare, for each one of a set of common conditions, visit outcomes between patients that saw the *same* provider, either in person or remotely. The strategy is served by the fact that even high adopters of remote medicine still saw many patients in the clinic during the post-lockdown period, and vice versa. The comparison of contemporaneous visits by the same provider addresses potential selectivity of the visit setting across providers and time. To account for the residual selectivity on the patient side, we will match remote and in-person cases based on their propensity to have the index condition, as predicted using a very

rich set of observable characteristics. Using this matched sample, we will estimate:

$$\textit{Outcome}_{ijtl} = \alpha \textit{Remote}_{ijtl} + \Gamma_j + \mu_t + \delta X_{ijtl} + \nu_{ijtl}, \tag{3}$$

where here, *Remote* refers to the actual visit setting, Γ_j is a physician (or match) fixed-effect, μ_t is a time fixed effect, and X_{ijtl} are patient controls.

To define medical conditions in a way that is robust to the endogeneity of a diagnosis of an index condition, we use symptom data from EMR records and consider groups of differential diagnoses (namely, the set of possible conditions that could be causing the same symptoms). This approach will allow us to evaluate the diagnostic precision of physicians across different settings. Furthermore, for some conditions, diagnostic mistakes are likely to be discovered in later encounters: a misdiagnosed pneumonia may result in a corrected later diagnosis, or in subsequent antibiotic prescription, ED visit, hospitalization, or death, all of which we observe.

Preliminary Results

The shift to remote medicine during COVID-19. Figure 1 shows the average weekly number of visits during the first part of 2020, for each of the 3,800 primary care physicians in Clalit who performed at least 100 visits in 2020. The lockdown period was associated with a sharp decline in total number of visits and a sharp increase in the number (and share) of remote visits: in the peak of the lockdown, remote medicine accounted for half of all visits. These patterns are consistent with the sharp decline in mobility in Israel during the lockdown period as shown in Figure 2, based on mobility data from Google. Post-lockdown, there was by a sharp bounce back in overall visits volume (and mobility), but the use of remote medicine remained at much higher levels than the pre-pandemic baseline.

Table 1 shows data on 1.5 million visits during the May–June post-lockdown period, of which 20 percent were remote. Panel A compared patient characteristics. Users of remote medicine are more likely to be female, older, and live in higher socioeconomic status zip codes. They have slightly more chronic conditions. Panel B shows the distribution of diagnostic categories by setting. The share of many categories for in-person and remote visits is fairly similar, though there are notable differences. As expected, patients are less likely to seek remote medicine for traumas and injuries. Remote medicine is more often used for conditions that are less likely to require physical attention, such as conditions related to the urinary tract or mental health conditions (though the share of the latter is small, because primary care physicians are not the main providers of mental health services). Figure 3 shows the distribution of estimates of the physician fixed effects, $\hat{\phi}$, from equation (1) showing ample variation in the tendency to provide remote medicine in March–April 2020, conditional on case mix.

Diagnosis and treatment of urinary tract infections in-person versus remotely. We focus the rest of this preliminary analysis on the subsample of urinary and renal conditions that are

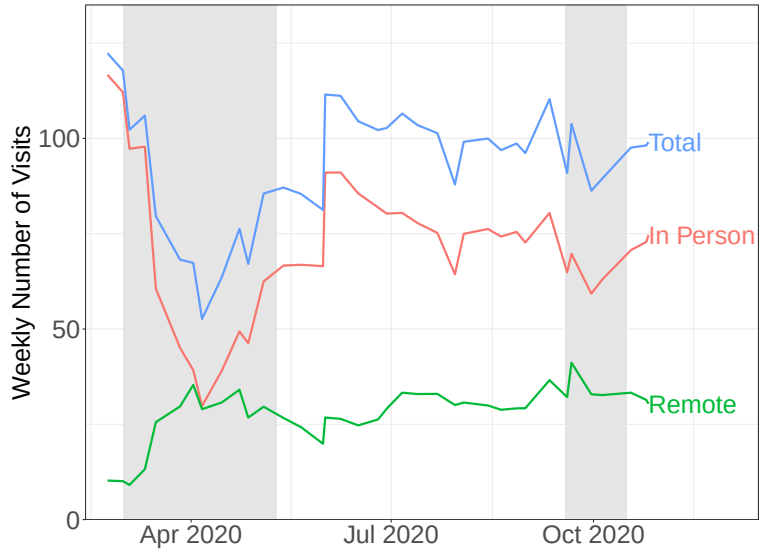
part of the differential diagnosis for Urinary Tract Infection (UTI), a common condition that is primarily caused by bacterial infection, and in uncomplicated cases, is treated with a short course of antibiotics. We chose UTI as an initial illustration since this is one of several common conditions for which we have a large sample of physicians who saw both remote and in-person patients. We sample all cases of UTI and differential diagnoses (selected with the help of a primary care physician in Clalit). Symptoms from a lower urinary tract infection include pain with urination, frequent urination, and feeling the need to urinate despite having an empty bladder. The differential diagnosis involves a host of other conditions, such as Candidal Vaginitis, a fungal infection, the differentiating of which is assisted by urine culture, a lab test.

We match all cases seen remotely by a physician to selected in-person cases by the same physician, using propensity score matching on gender, age, number of chronic conditions, ACG score, and different measures of past history of UTI. The weights for the propensity score were estimated using an auxiliary sample of visits from the same weeks in 2019 (the most important predictors of UTI are gender and recent history of UTI). Table 2 describes the pre-match and matched samples. After matching, conditional on observables, the probability of patients treated in person and remotely in our index 2020 sample to be diagnosed with UTI would have been identical in 2019 (43 percent).

Table 3 shows the results of estimating equation (3) on the matched sample, for different outcome measures. We find no significant difference in the probability of a UTI diagnosis, either within 30-day of of the index visit (Col. 1) or during the index visit (not shown), in the probability of an antibiotic prescription, or in the number of diagnosis codes recorded on the visit summary, a measure of diagnosis certainty. Remote patients are not more (or less) likely to be prescribed antibiotic treatment for a UTI. These null estimates are fairly precise. Remote visits are less likely to be referred to a lab test, perhaps because testing, which is done in person, is easier to perform on patients already in the clinic. Conditional on testing, there is no significant difference in urine culture test positivity rate (for UTI). Remote index visits are more likely to be followed by a remote visit to (any) doctor within a week and less likely to be followed by an in-person visit, suggesting follow-up visit setting is auto-correlated. The overall probability of a follow-up is not statistically different between remote and in-person index visits.

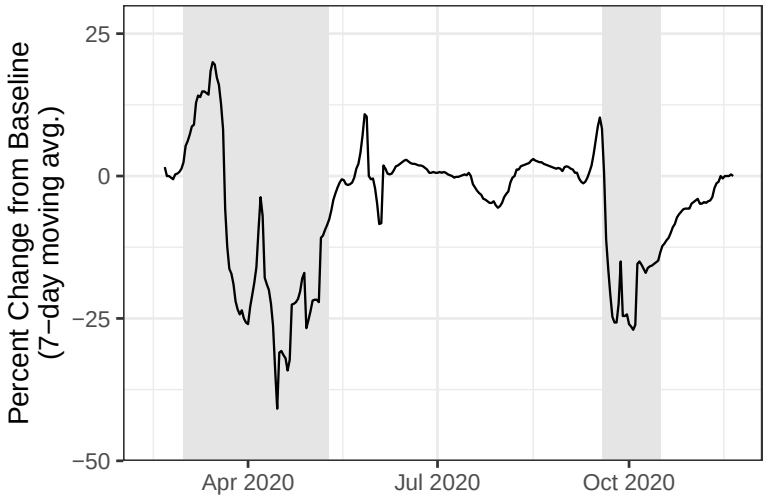
These results are preliminary and are meant to preview our planned analysis discussed above in detail, though they are suggestive—at least in the context of UTI—that remote medicine is here to stay, even in the post-pandemic era, as it may be just as effective as in-person visits and surely more convenient.

Figure 1: Weekly number of visits per primary-care physician in 2020



Notes: Figure shows the average weekly number of visit per physician in our sample, which consists of all primary care physicians active in 2020. Total (top line) shows the total nubmer of visits. In Person (middle) show the number of visits in physical clinics and, Remote (bottom) shows the number of consults via phone or video conferencing technology. The gray shaded areas mark the first and second government-imposed lockdown.

Figure 2: Mobility around the COVID-19 lockdowns in Israel



Notes: Figure shows the 7-day moving average Google mobility level associated with the use of pharmacies and grocery services, relative to the 2019 baseline. The gray shaded areas mark the first and second government-imposed lockdowns.

Figure 3: Physician April–March 2020 Tendency to Conduct Remote Visits Relative to Average, Residualized by Case Characteristics

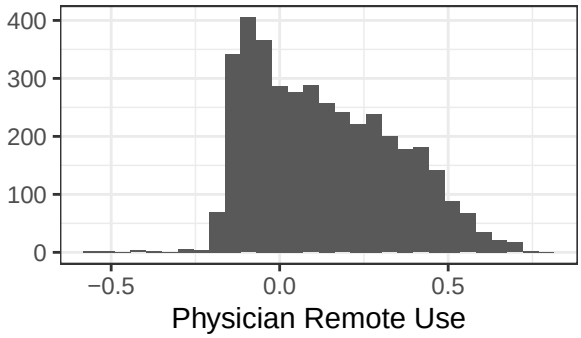


Table 1: Characteristics of Patients Visit by Setting, May–June 2020

	In Person	Remote
A. Patient Characteristics		
Female (Percent)	55.4	60.8
High SES (Percent)	27.9	42.6
Age (Mean)	42.7	46.1
ACG (Mean)	1.5	1.7
Number of CC (Mean)	3.5	4.1
B. Category of Diagnosis (Percent)		
Muscles and Skeleton	13.9	11.1
Ear, Nose, or Throat	13.0	10.1
Digestive	11.8	10.8
Endocrine, Immune, or Lymphatic	9.4	14.9
Heart and Blood Vessles	6.9	7.3
Respiratory	6.5	5.7
Injury/Wound/Trauma	6.9	3.7
Skin	6.0	3.7
Urinary/Renal	4.3	6.4
Brain/Neurological	4.6	4.6
Reproductive	2.2	2.6
Mental Health	1.9	2.5
Other	12.6	16.6
Number of Visits	1,153,962	305,962

Notes: Table shows data on non-follow up visits in the post-lockdown period between May 10, 2020 and the end of June 2020. A non-follow up visit is defined as a visit without any other visit in the two weeks preceding it. ACG denotes the score from the Johns Hopkins Adjusted Clinical Groups classifier (higher scores assigned to patients with higher predicted utilization). High SES denotes a patient living in a high socioeconomic zip code. CC denotes chronic conditions.

Table 2: Matched Sample of In-Person and Remote Visits, May–June 2020

	Pre-Match		Matched		Propensity
	In Person	Remote	In Person	Remote	Coeff (s.e.)
	(1)	(2)	(3)	(4)	(5)
Avg Propensity Score (UTI diagnosis probablity)	0.38	0.43	0.43	0.43	
Demographics					
Portion Female (Percent)	64.51	71.51	70.76	71.36	0.432***
Avg Age	45.93	46.90	51.37	54.40	0.155***
Health Characteristics					
UTI in Last Year (Percent)	18.89	22.51	26.93	24.80	0.210***
Number of UTI Months in Last 5 Yrs (Mean)	1.88	2.15	2.25	2.32	0.140***
Avg ACG	1.49	1.65	1.48	1.65	−0.055***
Num of CC	0.05	0.10	0.06	0.12	0.023**
Number of Docs	3,841	1,511	1,438	1,265	
Number of Visits	15,054	2,776	2,343	2,343	22,063

Notes: Table shows pre- and post-match selected characteristics of patients treated remotely and in-person during May–June 2020. Matching is performed based on pre-visit characteristics. Column 5 shows propensity score standardized coefficients.

Table 3: The Impact of Setting on Urinary Tract Infection Diagnosis, Testing, Prescription, and Follow-Ups

	Dependent Variable:						
			Urine Culture Test			7-Day Followup	
	UTI Diagnosed	Num of Dx Coded	Referral	Positive	Antibiotic Rx	Remote	In Person
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote	0.003	−0.004	−0.139***	−0.045	0.010	0.056***	−0.043*
	(0.022)	(0.034)	(0.025)	(0.043)	(0.022)	(0.016)	(0.022)
ACG	−0.006	0.005	0.007	0.003	−0.010*	0.003	0.004
	(0.005)	(0.008)	(0.006)	(0.012)	(0.005)	(0.004)	(0.005)
UTI in Last Year	0.144***	0.088**	0.031	−0.002	0.068***	0.030*	−0.013
	(0.023)	(0.036)	(0.026)	(0.044)	(0.023)	(0.017)	(0.023)
Gender (Male)	−0.307***	−0.028	0.039	−0.084*	−0.251***	−0.001	0.021
	(0.025)	(0.039)	(0.028)	(0.049)	(0.025)	(0.018)	(0.025)
Mean of Outcome	0.45	1.531	0.521	0.223	0.302	0.105	0.239
Observations	4,686	4,686	4,686	1,770	4,686	4,686	4,686

Note: *p<0.1; **p<0.05; ***p<0.01

Regs include age group, num of UTI's in last 5 years, num of CC, dummies for top 50 CC, and doctor FE

Notes: Table shows estimation results of equation (3) for the sample of May–June 2020 case with differential diagnosis of UTI.

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