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**Abstract**

We estimate the impact of increased access to telemedicine that followed widespread adoption during the March-April 2020 lockdown period in Israel (due to COVID-19). We focus on the post-lockdown period, which in Israel was characterized by a temporary return to normalcy. Prior to the lockdown, telemedicine accounted for about 5% of all primary care visits. It peaked at around 40% during the lockdown, and remained high, at around 20%, during the post-lockdown period. Using a difference-in-differences framework, we compare primary care episodes before and after the lockdown between patients with high and low access to telemedicine, with access defined based on their main primary care physician's propensity to adopt telemedicine during the lockdown. Increased access to telemedicine results in a 3.5% increase in primary care visits, but a 5% lower per-episode cost, so overall resource utilization is slightly lower. We find that remote visits involve slightly fewer prescriptions and more follow-ups, mainly with the same physician, which is consistent with a prolonged diagnostic path in the absence of physical examination. However, analyzing specific conditions, we find no evidence of missed diagnoses or adverse outcomes. Taken together, our findings suggest that the increased convenience of telemedicine does not compromise care quality or raise costs.

JEL codes: I11

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# 1 Introduction

Over the last two decades, telemedicine—the administration of health services remotely—has been touted by many as a potential tool to transform the provision of healthcare. Just like e-commerce has revolutionized retail, so the argument goes, telemedicine was going to revolutionize the healthcare industry (Dorsey and Topol, 2016).[1] Yet, as recently as early 2020, the adoption and use of telemedicine by both providers and patients had been largely limited to small-scale programs that targeted remote locations, late hours, or specific conditions (Tuckson et al., 2017). For example, in the United States, for various reasons, such as limited reimbursement, licensure hurdles, and state practice laws, remote visits accounted for less than 1% of primary care visits before 2020 and were typically not provided by the patients' regular primary care providers (Dorsey and Topol, 2016).

This state of affairs is likely to change after the COVID-19 pandemic, which has precipitated a rapid expansion of telemedicine. Since March 2020, healthcare systems throughout the world have substantially expanded the provision and coverage of remote medicine, leading to a surge in adoption (Alexander et al., 2020; Mehrotra et al., 2020b; Patel et al., 2020, 2021). In the United States, for example, the share of remote visits rose sharply once hurdles were swiftly lifted in the wake of the COVID-19 pandemic, peaking at nearly 30% of all visits in April 2020, before stabilizing at much higher levels than before the pandemic (Mehrotra et al., 2020a; Patel et al., 2020). The rapid growth of telemedicine and the the broadening of clinicians' licenses to use it raise the question of what will become of these new approaches to treatment once the immediate COVID-19 crisis has passed (Cutler et al., 2020; Dorsey and Topol, 2020).

Providing care remotely entails both risks and opportunities. On the positive side, telemedicine has the potential to improve access to care and to make care much more convenient (Hollander and Carr, 2020). It may also expand the geographic reach of providers and reduce the costs of follow-up encounters, supporting continuity of care. On the negative side, the ease of access to telemedicine might increase low-value utilization. Further, remote diagnosis without physical examination of patients could cause mistakes or increased use of specialist services or other costly substitutes to primary care (Ashwood et al., 2017; Li et al., 2021). Understanding these pros and cons is critical in guiding the future, post-pandemic use of remote medicine. In this study, we attempt to start filling this gap by taking advantage of

[1] Examples of media coverage include: Frakt, Austin, "You Mean I Don't Have to Show Up? The Promise of Telemedicine," *The New York Times*, May 16, 2016; Beck, Melinda, "How Telemedicine Is Transforming Health Care," *The Wall Street Journal*, June 26, 2016; Hansen, Claire, "The Telemedicine Revolution: A Crucial Component of Everyday Care," *U.S. News*, Novermber 2, 2017; "A Digital Revolution in Health Care is Speeding Up," *The Economist*, March 4, 2017.

a unique situation created in Israel during and shortly after the first COVID-19 wave, when widespread adoption of remote medicine was followed by a short period of nearly complete reopening.

The Israeli context is particularly useful for studying the impact of telemedicine. First, like most other countries, Israel moved to quickly facilitate the use of telemedicine during the first COVID-19 wave, resulting in a surge of adoption. By April 2020, about 40% of all primary care visits were provided remotely, and levels remained high thereafter (Figure 1). Second, Israel responded to the first COVID-19 cases in March 2020 with extremely quick and aggressive lockdown measures, which resulted in a successful (though temporary) mitigation of COVID-19. At the time, it was widely believed that Israel was approaching full suppression, leading to an equally quick and swift move to fully re-open the economy and return to normalcy, with schools, malls, and restaurants all opening in early May. These unique circumstances allow us to study the combined use of in-person care and telemedicine, when COVID-19 levels are low. Third, we obtained access to detailed medical records from Israel's largest healthcare provider, covering 12 million primary care episodes between January 2019 and June 2020. The data cover all the provider's enrollees, who account for more than half of the Israeli population. This allows us to observe a healthcare system in its entirety. It enables us to evaluate not only the impact of shifting to remote care during a single visit, but also the endogenous selection of providers, the use of subsequent healthcare services, and the impact on health outcomes, diagnosis accuracy, and total cost of care.

The key challenge to studying the impact of remote medicine is that the in-person versus remote setting for a primary care visit is, naturally, endogenous. Patient and provider inclination to use telemedicine surely depends on the medical characteristics of each case. For example, remote visits have an outsized share of mental health complaints and a smaller share of ear, nose, and throat complaints, because the former require no physical exams to handle, whereas the latter do. To address this challenge, our empirical strategy does not rely on the actual visit setting but instead focuses on patients' *access* to telemedicine, which we measure based on the decision of a patient's regular primary care physician to adopt telemedicine. To measure physician adoption, we use their tendency to shift to remote care during the COVID-19 lockdown period (March-April 2020), adjusting for case mix, time, and place. Based on this analysis, we consider physicians whose adoption was above median as *high adopters* and the rest as *low adopters*, and their patients as having *high* and *low* access, respectively, in the post-lockdown period (May-June 2020). Indeed, patients affiliated with high adopters were much more likely to have remote visits in the post-lockdown period: 30% of their primary care visits were conducted remotely, compared to only 8% for patients of low adopters.

We use this variation in telemedicine access to implement a difference-in-differences approach and compare outcomes of primary care visits and the ensuing episodes before and after the lockdown between patients with high and low access to telemedicine. Thus, we allow the choice of setting to be endogenously determined by patients and providers, a likely scenario under future policies. Our difference-in-differences design also allows high telemedicine adopters to have different practice styles than low adopters, as long as their trends over time are similar (and they are). Placebo analyses further support the assumptions underlying the research design.

Our findings suggest that increased telemedicine access is associated with a modest, 3.5% increase in the utilization of primary care, and this increased use is offset by lower episode intensity. The overall cost of services utilized during the 30 days following an initial primary care visit is 5% lower, so overall healthcare costs slightly decrease. We find that access to telemedicine has only a modest impact on visit outcomes: patients with higher access to telemedicine receive slightly fewer prescriptions and referrals to other providers. We find no significant difference in the probability of referrals to laboratory tests or to the emergency department (ED). And while access to telemedicine is associated with a slight increase in the number of follow-up visits, such visits are predominantly with the same physicians that provided the initial visit. Overall, our findings are consistent with physicians' taking somewhat longer to complete diagnostic processes in some cases. Furthermore, a significant share of follow-ups—including ones that would have likely happened even without telemedicine access—shift to remote visits.

We explore the extent to which the results vary across different types of patients and medical conditions. Among other things, we show that the results are quite similar when we focus on conditions that are acute and less deferrable. This is particularly reassuring because a plausible concern about the research design is that the lockdown made patients defer primary care encounters—perhaps even more so for patients whose physicians did not use much telemedicine. The finding that the results are similar for less deferrable conditions suggests that this concern is unlikely to drive the main results. We also reproduce our findings using an alternative (and slightly longer) post period in 2021, after a successful vaccination campaign that has lead to a full reopening. During this period, which is presumably shadowed less by COVID-19, telemedicine use—and its estimated impacts on the outcomes we observe—remain very similar as in our baseline analysis, which is reassuring.

The increase in the probability of follow-ups raises the possibility that physicians are less certain in diagnoses given remotely. A related concern is that remote visits may involve more errors, such as misdiagnosis or missed diagnoses. To explore this possibility, we analyze in more detail the diagnosis and treatment of three medical conditions: urinary tract infections, heart attacks, and bone fractures, which we chose because they are common and, more important, because false negative cases are likely observed (absent treatment, all three conditions would involve aggravating symptoms that would lead patients to seek further care). Across all three conditions, we cannot detect any evidence for missed diagnoses or adverse outcomes.

Taken together, our findings suggest that access to telemedicine does not substantially alter the utilization or outcomes of care. Physicians appear to properly diagnose and treat the marginal low severity cases that telemedicine brings rather than overtreat or refer them. More broadly, the results suggest that providing patients access to telemedicine can productively complement in-person primary care.

We are obviously not the first to study the impact of telemedicine, but given the limited nature of telemedicine use prior to COVID-19, the scope of earlier work is narrower. For example, Shi et al. (2018), using US commercial insurance claims data, match 40,000 direct-to-consumer telemedicine visits of adults with acute respiratory infection diagnoses with in-person visits in primary care and urgent care settings. They find that telemedicine visits have similar rates of antibiotic use as in-person visits, but less-appropriate streptococcal testing and a higher frequency of follow-up visits. In contrast, Ray et al. (2019), who match 4,500 pediatric telemedicine visits for acute respiratory infections with in-person visits, find that telemedicine visits have higher antibiotic prescribing and lower guideline-concordant antibiotic management. Other works have focused on patient response and substitutability with in-person care. For example, Player et al. (2018) find that most patients surveyed after an e-visit at the Medical University of South Carolina in 2015–2017 reported a positive experience and that had, in their view, replaced an in-person visit. Shah et al. (2018) also find that virtual visits partly replace in-person visits in a Massachusetts-based accountable care organization in 2014–2017. In contrast, Ashwood et al. (2017), matching telemedicine and in-person visits, estimate that only 12% of direct-to-consumer telemedicine visits replace visits to other providers. Analyzing commercial claims for 2016–2019, Li et al. (2021) find that compared to in-person visits, telemedicine visits for acute respiratory infection involve more downstream care. A meta-analysis by Shigekawa et al. (2018) concludes that the impact of telemedicine interventions on the use of other services remains unclear.

Our research design is different from existing works in that we exploit the variation in recent adoption of telemedicine rather than matching cases across settings. Given the sharp increase in telemedicine use due to COVID-19, the scale and breadth of our data is much larger than these earlier important studies. The data we use cover the provision of remote visits in almost all aspects of primary care, rather than specific conditions, and they covers synchronous visits that are provided, for the most part, by the patients' regular primary care physicians, as opposed to asynchronous visits or visits provided by dedicated clinicians in specialized telemedicine clinics. This nature of broader telemedicine deployment seems more similar to the likely future use of telemedicine in the post-pandemic era.

The rest of the paper proceeds as follows. Section 2 discusses the setting and data. Section 3 discusses our empirical strategy, and Section 4 presents our main results. Section 5 discusses additional robustness and heterogeneity analyses, and Section 6 concludes.

# 2 Setting and Data

## 2.1 Background

Israel confirmed its first COVID-19 case on February 21, 2020, and quickly put in place multiple measures to clamp down the spread. Panel A of Figure 2 displays the 7-day moving average of daily new confirmed COVID-19 cases. In response to a rapid increase in the number of confirmed cases, Israel shut down all schools and universities on March 12 and announced a state of emergency on March 19, effectively closing much of the country. Further tightening occurred on March 25 when it was announced that individuals could not go further than 100 meters from their homes except for essential services. These measures, in addition to limits on international travel and relatively high compliance by the population, led to a swift drop in cases and a rapid return to normalcy. By early May, the test positivity rate fell to 1% from its high of over 10% in late March, and daily new confirmed cases fell to as low as single digits (see Panel A and Panel B of Figure 2). At the time, Israel was widely seen as a model for how to successfully contain the spread of COVID-19.

With the virus seen as largely contained, Israel quickly began reopening the economy and education system in late April and early May. Retail restrictions were eased beginning in late April.[2] Schools began reopening on May 3 and were fully open by May 20. On May 7, malls and markets opened, and by late May, restaurants opened for indoor dining, and gyms and large public pools were opened for indoor exercise. Addressing the nation after a period with only a handful of daily confirmed COVID-19 cases despite extensive testing, Benjamin Netanyahu, Israel's prime minister, famously urged Israelis to "get out, return to normalcy, ... have fun."[3] Panel C of Figure 2, based on Google Mobility data, shows that visits to groceries and pharmacies returned to baseline, pre-COVID levels. Panel D of Figure 2 shows the average daily number of visits seen by primary care physicians, demonstrating that total visit volumes returned to nearly pre-COVID levels, further supporting the fact

[2] "IKEA opens half of stores in Israel after lockdown eased." *Reuters*, April 22, 2020.

[3] "Netanyahu to Israelis: Have Fun, We're Easing Coronavirus Restrictions," *The Jerusalem Post*, May 26, 2020.

that behavior during this period broadly represents the "back to normal" environment and is not significantly influenced by COVID-19 concerns.

Daily case rates began ticking up in June, but additional social distancing measures were not reinstated until early July. Israel ultimately experienced additional waves of COVID-19 associated with much higher numbers of cases and deaths. Nonetheless, the short period of the partial (and temporary) return to normalcy following the very successful mitigation of the first COVID-19 wave was characterized by a widespread belief that full suppression was imminent, ans so we view it as a useful emulation of the post-pandemic era. Particularly useful is the combination of increased (and heterogeneous) access to telemedicine and low threat of COVID-19.

Guided by this context, we split our sample into three periods.[4] First, the pre-COVID period between January 7, 2019, and March 1, 2020, which we refer to as the *pre-lockdown* period. Second, we define the period between March 2, 2020, and May 10, 2020, characterized by extreme restrictions on mobility, economic activity, and healthcare use, as the *lockdown* period. Finally, we use the four-week period of relative normalcy between May 11, 2020, and June 7, 2020, as the *post-lockdown* period, covering the time between the lifting of major restrictions and the time when the number of daily cases started climbing again.

## 2.2 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. Universal coverage broadly resembles that of Medicare parts A, B, and D and includes hospital admissions, outpatient services, physician consults, prescription drugs, and durable medical equipment. Clalit covers over one-half of the Israeli population, approximately 4.5 million members of all ages. It is an integrated payer and provider, providing most of the services it finances by salaried providers and reimbursing services purchased from external providers. All four HMOs offer identical coverage but use distinct provider networks to do so, with the exception of hospitals, which are used by all four. In principle, members can switch HMOs up to twice a year and maintain their universal coverage, but the annual switching rate is extremely low (around 1%), so each HMO covers a very stable population of members.

In the years prior to 2020, Clalit sought to expand its use of telemedicine but, as in the rest of the world, progress was slow and the scope and utilization of remote care was limited. Service was limited to specialized, after-hours, direct-to-consumer clinics. Physicians did

[4] Because utilization exhibits strong weekly periodicity, all periods begin on a Monday and their lengths are multiples of 7 days.

occasionally call patients, for example, to follow up on matters such as lab test results. Patients could not, in general, remotely visit their regular primary care physicians; they had to schedule an in-person appointment to do so.[5]

Throughout the first COVID-19 wave, health clinics remained open and physicians were still able to see patients in person. However, patients and physicians were encouraged to conduct telemedicine visits whenever possible. Since the first wave, patients have been able, for the first time, to choose between an in-person and remote setting when visiting office-based physicians, based on the mix between the two that the physician chooses to offer. The majority of remote visits are conducted via phone, though some physicians also use video conferencing technology. Because we do not observe the communication platform used, we refer to all synchronous remote visits as "telemedicine visits." These visits are equivalent to in-person visits for reimbursement purposes and do not differentially affect physicians' pay.[6] As shown in Figure 1, the telemedicine share of visits increased sharply from a pre-COVID level of 6% to around 40% in mid-April. After the lockdown ended, the share of remote visits fell and plateaued at about 20%, well above the pre-COVID baseline.

Clalit maintains detailed and comprehensive claim-level data associated with all the services it provides or reimburses to its universe of members, similar to billing data in the United States. Clalit also maintains electronic medical records (EMR) data on its patients, which include diagnoses, lab test results, and vital sign measurements. Universally covered services are fully subsidized (HMOs receive risk-adjusted capitated payments from the government for each individual they enroll). Throughout our study period, all primary care visits, both in-person and remote, were fully covered and did not have associated co-pays.

**Study Sample.** To construct the study sample, we include all Clalit physicians who serve as primary care providers for both adults and children. We then include all covered members

[5]Since 2015, patients have had the ability to consult primary care, pediatric, and dermatology specialists regarding minor acute conditions via remote channels (voice or video chat). However, this service was limited to after hours and was intended mainly as a mode of triage, with physicians having no prior or subsequent interaction with patients. During the period between 2015 and 2020, this service accounted for 0.25% of all primary care visits. Since 2015, Clalit has also offered a patient portal, where patients can submit requests to their primary care doctor for prescription refills or other administrative tasks. Such requests are answered asynchronously within five business days and are not used for diagnosing new conditions. This functionality has not changed during the period of this study.

[6]Primary care physicians in Clalit receive a global compensation that is a combination of a baseline salary that depends on tenure and compensation component that is proportional to the number of attributed patients and time slots that are regularly available for patients. That is, physician compensation is not directly tied to the number of visits they provide, either in-person or remotely. When accounting for these visits in cost calculations, Clalit (and this study) uses per-visit charges that are based on customary charges by non-employed providers. During the period of our study, these charges were the same for in-person and remote visits. Specialists are reimbursed according to a pay schedule, which during the study period was the same for in-person and remote visits.

for which one of these 4,293 physicians serves as their main primary care provider, defined as the provider each member saw the most in 2019 (see Appendix A for more details). For these 4.3 million members, we extract all healthcare utilization during the study period, January 2019 through June 2020. We use this sample to study the impact of telemedicine on overall utilization and cost of care.

Our main study sample, which we use for studying visit and episode outcomes, includes all patients who had one or more primary care episodes during our study period (in the context of their interactions with medical providers, we refer to Clalit members as patients; all patients in our study are also Clalit members). We define a primary care episode as a 30-day period that starts with a synchronous primary care visit, in either a remote or in-person setting. We refer to this first visit in an episode as the *index* visit. We restrict attention to *new* care episodes by including only episodes that start with a non-follow-up index visit, namely, a visit without any health care encounter (hospital visit, physician visit, or lab test) in the 14 days preceding it. Such non-follow-up visits account for 44% of all primary care visits. Appendix A provides more detail on these definitions and on the construction of this sample. The resulting sample includes 12 million care episodes involving 3.7 million patients.

We split this sample into three main sub-periods, according to the timeline of the COVID-19 lockdown discussed in Section 2.1. Our main focus is on half a million primary care episodes that started during the post-lockdown period, which we compare to 10.4 million primary care episodes that started during the pre-lockdown period, or in some cases against episodes that started during the same date range (May 11 to June 7) in 2019. Appendix A discusses the sample and study periods in detail.

**Main Variables.** We consider the effect of access to telemedicine on several sets of outcomes. The first outcome is utilization and total cost of care for all members. We record utilization for each covered member during the pre- and post-lockdown periods as an indicator variable, which is equal to 1 if the member used healthcare services (of any type) during the period and 0 if the patient did not use care at all. Total cost is the sum of the total cost of services used. All costs are denominated in current New Israeli Shekels (NIS).[7] Second, we observe the outcomes of the index visits that started primary care episodes: prescriptions, test orders, and referrals to other providers. Third, for each primary care episode, we also count the number of follow-up visits that occur during the 7 days following the index visit; we include follow-up visits with either the same physician as the one providing the index visit or other physicians, either remotely or in-person. Finally, we associate each episode with utilization and cost of all services during the 30 days following the index visit. We break

[7]During the study period, the exchange rate was approximately 3.6 NIS per USD.

down costs to the following categories: prescription drugs, primary care, lab and imaging, specialists, outpatient, emergency department, inpatient urgent, inpatient elective, and all other services. In our main analysis, we use the following control variables: gender, five-year age group, the Johns Hopkins ACG risk score (a commercial risk classifier that measures predicted future healthcare utilization), number of diagnosed chronic conditions, subdistrict, and category of diagnosis. Appendix A provides detailed definitions of all variables.

**Summary Statistics.** Table 1 presents visit summary statistics for sampled index visits in the post-lockdown period by visit setting: remote or in-person. Out of the 560,000 sampled visits, 18% were telemedicine visits; the rest were in-person visits. Panel A shows data on patient characteristics. Compared to in-person visits, telemedicine visits had patients who were 4 percentage points more likely to be female, have much higher socioeconomic status (SES), were about three years older on average, and had slightly higher ACG risk scores and a slightly greater number of chronic conditions. These differences suggest that remote visits do not have the same mix of complaints and health issues (see Appendix Figure A1), further highlighting the need to account for this selection in the study design.

The difference in SES—determined by the patient place of residence, based on classification by Israel's Central Bureau of Statistics—is remarkable, with 42% of remote visits being conducted with patients from the top SES tercile, compared with only 26% of in-person visits.[8] It highlights the need to account, as we do, for variation across location in telemedicine adoption.

The remaining panels of Table 1 further compare physicians' decisions, follow-ups, and service utilization and cost over the subsequent 30 days between remote and in-person (index) visits. In-person and remote visits slightly differ on all these measures. These differences in outcomes may reflect differences in the case mix. Panel B shows data on visit outcomes. Remote visits involve significantly fewer prescriptions (38.2% versus 53.1%), more lab tests (32.4% versus 30.9%), and fewer referrals to other providers (e.g., 0.5% of remote visits are referred to the emergency department versus 0.8% of in-person visits). Panel C shows data on the average number of physician visits in the 7-day period after the index visit. Episodes starting with a remote index visits involve a greater number of follow-ups (0.38 additional physician visits, compared with 0.33 for episodes starting with an in-person visit). Compared to in-person visits, remote visits have three times more remote follow-ups (0.13 for remote versus 0.04 for in-person). Panel D shows data on overall costs. Over the 30 days following the index visit, episodes starting with a remote visit have a higher total spending on average than episodes starting with an in-person visit (688 NIS compared to 657 NIS).

[8] Patel et al. (2021) document similar patterns in the United States.

# 3 Empirical Strategy

Naturally, the choice of remote versus in-person setting for a primary care visit is likely endogenous. Therefore, our empirical strategy does not rely on directly comparing remote to in-person visits, but instead takes advantage of variation in patients' access to telemedicine.

Specifically, the strategy consists of three steps. First, for each primary care physician in the sample, we estimate her propensity to adopt telemedicine during the lockdown period. Second, we split the patient population into those whose primary care physicians had a high propensity to adopt telemedicine and to those whose primary care physicians had a low adoption propensity and compare the two patient populations in the post-lockdown period. Finally, to account for potentially unobserved differences between the patient populations of high-telemedicine and low-telemedicine physicians, we apply a difference-in-differences strategy using data on the pre-lockdown period.

This section discusses the underlying measurements, estimation procedures, and identification assumptions.

## 3.1 Measuring Physician Adoption of Remote Care

We first estimate, using data on all visits conducted by physicians in our sample during the *lockdown* period, each physician's propensity for conducting remote visits:

$$\text{Remote}_{ijtl} = \alpha_j + \tau_t + \eta_l + \gamma X_{it} + \nu_{ijtl}, \tag{1}$$

where $i$, $j$, $t$, and $l$ are indices for the index visit of patient $i$ with physician $j$ at time (week) $t$ and location (subdistrict) $l$. $Remote_{ijtl}$ is an indicator for a remote visit; $X_{it}$ denotes visit controls, including patient age, gender, number of chronic conditions, ACG score, and diagnosis category; and $\tau_t$ and $\eta_l$ are week and subdistrict fixed effects. The estimated physician fixed effects, $\alpha_j$, serve as our measure of the tendency of each physician to shift to remote care during the lockdown period.

Figure 3 shows the distribution of raw and residualized physician use of telemedicine during the lockdown period. Panel A of Figure 3 shows the distribution of the raw share of visits that each physician in our sample conducted remotely. It reveals marked heterogeneity among physicians in their tendency to use telemedicine: while about 20% of physicians had zero or very few telemedicine visits, about a sixth shifted the majority of their practice to be remote during the lockdown period. Panel B of Figure 3 shows the distribution of estimated physician fixed effects ($\alpha_j$ from equation (1)). Accounting for time, location, and visit characteristics, the tendency of physicians in our sample to adopt telemedicine exhibits a fairly symmetric distribution around the median, $-0.01$, which we use below to classify physicians as high or low adopters. We henceforth refer to this estimated $\alpha_j$ as the physician's *telemedicine adoption*.

Table 2 presents summary statistics on the characteristics of high and low adopters and their case mix during the post-lockdown period. Compared with low adopters, high telemedicine adopters are far more likely to be female, somewhat younger, and more likely to specialize in family medicine (rather than in pediatric medicine). Telemedicine adoption, measured during the lockdown period, is also predictive of physicians' propensity to use telemedicine in the post-lockdown period. Relative to low adopters, who handle only 6% of their post-lockdown cases remotely, high adopters handle 32% of their post-period visits remotely. Panel B shows data on the distribution of characteristics of (index) primary care visits of the patients affiliated with each group of physicians in the post-lockdown period. Patients of high telemedicine adopters tend to be older and sicker (they have higher ACG scores and more chronic conditions). They are also more likely to come from high socioeconomic status and are more likely to be female. These differences highlights the need to account for differences in characteristics and case mix between high and low adopters and their patients.

Physician telemedicine adoption predicts future utilization of telemedicine by their patients. Patients whose main primary care physician had above-median adoption during the lockdown period conducted 30% of their primary care visits remotely during the post-lockdown period, compared to 8% for patients of below-median adopters.

## 3.2 Estimating The Impact of Increased Telemedicine Access

The key challenge for identification is that the in-person versus remote setting for a primary care visit is naturally endogenous. To address this challenge, our empirical strategy does not rely on the actual visit setting but instead focuses on patients' *access* to telemedicine, measured based on the telemedicine adoption of their primary care physician. That is, we classify physicians as high telemedicine adopters based on whether their estimated $\alpha_j$ from equation (1) is greater or less than the median:

$$\text{High}_j = \begin{cases} 1 & \text{if } \alpha_j > \text{median}_k \, \alpha_k \\ 0 & \text{otherwise.} \end{cases}$$

This measure is then used as a proxy for access to telemedicine for all their affiliated patients in the post-lockdown period. Namely, let $j(i)$ denote the main primary care physician of patient $i$. We say that patient $i$ had *high access* to telemedicine if and only if $\text{High}_{j(i)} = 1$.

We then consider how telemedicine access affects the outcomes of patients across *all* their visits during the post-lockdown period, regardless of either the actual visit setting (remote or in-person) or the identity of the physician conducting the visit.

Physician adoption of telemedicine, which we use as a proxy for patient access, may be endogenous too. For example, as we have described, it is correlated with other physician characteristics, such as physician age and gender, and different patient composition. This motivates our use of a difference-in-differences approach, which addresses this endogeneity concern by comparing post-lockdown outcomes for patients of high and low adopters against the patterns observed in the pre-lockdown period, when telemedicine was rarely practiced.

That is, to estimate the impact of access to telemedicine on care outcomes, we use the following difference-in-differences specification:

$$\text{Outcome}_{it} = \beta \text{High}_{j(i)} \cdot \text{Post}_t + \mu_{j(i)} + \zeta_t + \omega_{l(i)} + \delta X_{it} + \varepsilon_{it}, \tag{2}$$

where $j(i)$ is the main primary care physician of patient $i$, and $l(i)$ is patient $i$'s location (subdistrict); $High_{j(i)}$ indicates the patient's telemedicine access, which is interacted with $Post_t$, a dummy for the post-lockdown period; $\mu_{j(i)}$, $\zeta_t$, and $\omega_{l(i)}$ are physician, week, and subdistrict fixed effects; $X_{it}$ are visit controls. The parameter of interest is $\beta$, which captures the impact of access to telemedicine. It is estimated as the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine.

We use this same specification across our different study samples and different outcomes within each sample. In all analyses, we use only data from the pre- and post-lockdown periods and exclude the lockdown period, both because during this period telemedicine adoption was ramping up and because this period involved mobility restrictions and was overshadowed by the COVID-19 emergency, presumably affecting both the provision and demand for health care in unique ways. This also guarantees that there is a clear separation and no mechanical link between our measure of physician propensity to adopt telemedicine (which is based on lockdown behavior) and the main analysis (which is based on behavior pre- and post-lockdown).

## 3.3 Potential Concerns

The key identification assumption is that, if not for the impact of telemedicine, high and low telemedicine adopters would have had otherwise similar trends in their medical practice, and their patients would have had otherwise similar trends in morbidity during the post-lockdown period. Supportive evidence for this assumption comes from examining pre-trends in physician practice, using a version of the model in equation (2) with flexible lags and leads.

Figure 4 shows flexible estimates of time trends for the three most common visit outcomes (estimates for all other visit outcomes and for 7-day physician follow-ups are shown in Appendix Figure A2 and Appendix Figure A3). Despite marked (common) temporal variation in the weekly means of different outcomes in the pre period, the correlation between pre-lockdown outcomes of the high and low access groups is greater than 0.90 for all outcomes. Namely, high and low adopters of telemedicine seem to respond similarly to external factors, such as seasonal diseases. Consequently, they have pre-trends in care decisions and patient outcomes that are nearly parallel: Throughout 2019 and early 2020, the demeaned difference in outcomes rarely varies by more than a few percentage points over the pre-period mean and is extremely flat.

Residual concerns about the research design are related to the validity of the parallel-trends identification assumption in the post-lockdown period, where it is (as with any potential outcomes framework) not directly testable. It would be violated if patients of high and low telemedicine adopters had disparate outcomes in the post-lockdown period for reasons other than their access to telemedicine. One plausible concern in our specific context is that patients of low adopting physicians had greater difficulty in accessing their physician during the lockdown period and thus may have been more likely to defer care and consequently had differentially more pent-up demand post lockdown. We explore this concern by showing separate results for medical conditions that are less likely to be deferrable.

A different, more standard concern is one of reverse causality. Namely, that physicians may have adopted telemedicine in response to idiosyncratic shocks to their patients' health. This concern seems less relevant in our case given that, as we describe above, we measure physician adoption during the lockdown period while we estimate the impact of adoption on episodes that started after the lockdown period ended.

Finally, one may worry that telemedicine adoption may drive patient choice of providers—and therefore providers' case mix—in the post-lockdown period. However, as described in Appendix A, we construct patient-physician relationships based on the pre-lockdown period (when telemedicine was hardly used) and hold it fixed throughout the analysis. We also report below (in Section 5.1) reassuring results from auxiliary analyses, in which we use "placebo" post-periods (from before telemedicine adoption).

# 4 Results

## 4.1 Utilization and Total Cost of Care

Table 3 presents the results of estimating equation (2) for two outcomes: care utilization (namely, the probability of any use) and total cost of all services.[9] We find that access to telemedicine is associated with a small (0.3%) increase in the probability of any healthcare utilization. Despite this modest increase in utilization, access to telemedicine is associated with 3% lower total cost of care per member.

As shown in Table 3, the results are qualitatively similar when we restrict attention to primary care episodes only, which are the focus of the rest of this section. Greater access to telemedicine is associated with a 3.6% increase in the share of members who have a primary care episode, but the per-member cost of such episodes (averaged across all members, including those with no episodes) decreases by 5.7%. These findings are consistent with high-access cases being treated with lower average intensity (we further explore—and confirm—this hypothesis in the next section), suggesting that the marginal increase in utilization is coming from less severe cases.

## 4.2 Visit and Episode Outcomes

**Index Visit Outcomes.** Panel A of Figure 5 presents the results of estimating equation (2) for different outcomes associated with the index visits (that is, visits that start new care episodes). Such visits are of particular interest because they typically involve the diagnosis of the case and determine the course of treatment. Compared to the pre-lockdown period, in which 57% of index visits included a prescription, 25% included a lab test referral, and 8.5% included a referral to another physician (typically a specialist), index visits of patients with high access to telemedicine involve 5% fewer prescriptions (a 2.9 perentage point reduction) and fewer referrals to outpatient providers (4.6% fewer physician referrals, 9.5% fewer imaging referrals, and 4.5% fewer referrals to other non-physician outpatient providers). Relative to the pre-lockdown level, high-access patients also have 3.5% fewer referrals to the emergency department (although this last estimate is not statistically significant). There is no impact on referrals to lab tests.

These changes in visit outcomes brought by telemedicine access are modest in size. Estimates are much smaller in magnitude than the standard deviation of the outcome across

[9] As discussed in Section 2.2, this analysis is using the sample of all Clalit members, including those with zero utilization. Each member is associated with two observations: one for the post-lockdown period (in 2020) and one for the corresponding period in 2019.

physicians (in the pre-lockdown period), which is a measure of the general variability of visit outcomes. The decrease in prescriptions constitutes less than a third of the standard deviation in prescription rates across physicians. The effects on referrals are less than a sixth of a standard deviation in referral rates across physicians. These estimates suggest that providing care remotely does not significantly alter physician decision making during the index visit.

**Physician Follow-Ups.** Panel B of Figure 5 presents estimates of the impact of increased telemedicine access on the number of follow-up encounters with physician providers (of all medical specialties) within 7 days of the index visit. Access to remote care is associated with a 8.2% increase in the total number of follow-up encounters (relative to the 0.31 average number of such follow-ups in the pre-lockdown period). While in the pre-lockdown period only about half of these follow-ups are with the same physicians that conducted the index visit, more than 80% of the *increase* in follow-ups is concentrated in encounters with the index-visit provider.

These results may be related to the reduction in prescriptions and referrals associated with increased access to telemedicine, which we documented above. It is consistent with the hypothesis that remote cases take somewhat longer to resolve. But the process does not appear to increase care fragmentation. In fact, telemedicine may facilitate care management because it shifts follow-ups to remote visits, making them more convenient: access to telemedicine is associated with a 13.5% increase in remote follow-up visits and a 5.3% decrease in in-person follow-up visits (relative to the 0.31 average total number of follow-ups in the pre-lockdown period).

**Cost and Utilization.** Notwithstanding the increase in follow-ups, and consistent with the previous findings of an overall reduction in the cost of care, the overall intensity of care episodes is lower for patients with high access to telemedicine. Figure 6 shows the estimated impacts of telemedicine access on cost and utilization over the 30 days following the index visit. High telemedicine access is associated with a 5.1% decrease in total cost per episode (a decline of 29 NIS per episode, relative to the pre-lockdown level of 565 NIS). This impact on episode cost is quite modest: it amounts to less than a tenth of the standard deviation of total episode cost across (index) physicians. Cost is either lower or unchanged across nearly all spending categories, except for primary care visits, the cost of which slightly increases. Panel B shows that this small reduction in total episode cost reflects a reduction in utilization, which is to be expected given that service prices are common to all patients and fairly stable. In this regard, the negative effect of telemedicine access on episode cost is conservative: in our study, remote visits are priced at the same rate as in-person visits, despite the potential savings on facilities and equipment associated with remote medicine.

## 4.3 Diagnostic Accuracy

Even though shifting care remotely is not associated with substantial changes in the intensity of care, it may still entail some decrease in diagnostic accuracy due to the absence of direct contact with the patient. But assessing diagnostic quality using our main sample of all primary care episodes is challenging given the wide array of patient conditions covered, which may require different diagnostic procedures that resolve over different timelines. To gain insight, we focus on specific medical conditions and conduct a more granular analysis of the diagnostic process of three medical conditions: urinary tract infection (UTI), acute myocardial infarction (AMI, also known as "heart attack"), and bone fractures.

To account for the endogeneity of the diagnosis itself—particularly, for the possibility that physicians may be less accurate in remote settings—we sample each target condition together with all related conditions that share similar symptoms with it (and are therefore part the corresponding differential diagnosis). Appendix Table A1, Appendix Table A2, and Appendix Table A3 show the respective lists of target and differential diagnoses that were included in each subsample. Appendix B provides additional details on the construction of these samples.

We selected these specific conditions for three main reasons. First, they are fairly common and are observed in both remote and in-person visits. Second, in contrast to, for example, Streptococcal throat infection or respiratory infections, these three conditions share few symptoms with COVID-19 infections, reducing concerns that uncertainty about the diagnosis of the then-new disease would confound our analysis. Third, if any of these conditions is left undiagnosed during the index visit, aggravating symptoms would likely send patients to seek additional care. Therefore, comparing the rates of diagnosis of the target condition during the index visits with diagnosis rates over the subsequent 30-day period provides a measure for false negative diagnoses.[10]

The focus on specific conditions also allows us to control for risk factors and to consider outcomes that are specific to each target condition. For example, in the analysis of UTI, we control for patient history of UTI (a risk factor) and consider as outcomes referrals to urine tests (the most common diagnostic test) and antibiotics specific to UTI (the main treatment). Appendix Table A4 shows detailed summary statistics that specify all risk factors, diagnostics, and outcomes we use for each of the subsamples, which are further

[10] A similar idea is used in Abaluck et al. (2016), Mullainathan and Obermeyer (2019), and Chan et al. (2019).

discussed in Appendix B. A caveat in restricting the analysis to specific conditions is that sample sizes are, naturally, much smaller ($N = 14,877$ for UTI-related cases, $N = 10,105$ for AMI-related cases, and $N = 8,550$ for fracture-related cases).

Table 4 shows estimates of the impact of access to telemedicine on the diagnosis and treatment of each of the three conditions. Columns 1–4 show results for UTIs. In the pre-lockdown period, 40.3% of cases with UTI-related symptoms were diagnosed as a UTI during the (predominantly in-person) index visit, while 43.4% of these cases were diagnosed within 30 days of the index visit. That is, some diagnoses occurred after the index visit. However, we cannot detect any significant impact of remote medicine on either of these rates (telemedicine access has an estimated impact of 0.8 percentage points and 1.0 percentage points on index and 30-day diagnoses rates, respectively; both estimates are not statistically significant). Compared with the baseline practice, access to remote care does not appear to involve more missed UTI diagnoses.

Considering physician use of diagnosis codes in visit summaries can also shed light on how thorough their interaction is with the patient and how certain they are in the findings. We measure two related statistics: (i) the average number of distinct diagnosis codes recorded on the visit summary, and (ii) how specific these codes are. In the pre-lockdown period, physicians recorded an average of 1.6 diagnosis codes for UTI-related visits. About half of these codes refer to specific medical conditions (e.g., "cystisis", an inflammation of the bladder) whereas the rest represent less specific symptoms (e.g., "dysuria", discomfort or burning sensation when urinating, a symptom associated with multiple medical conditions). As shown in Panel A of Table 4, neither the total number of codes nor the share of less specific symptoms significantly changed with access to telemedicine.

Interestingly, despite having no impact on diagnosis rates, telemedicine access is associated with a 4.1 percentage point increase in the probability of referrals to urine tests during the index visit (a 10% increase over the baseline of 41%, though this estimate is not precise), and with a similar increase in the performance of urine tests during the episode. For UTI-related cases, we find no significant impact on prescription of antibiotics, either during the index visit or during the subsequent 30 days. Nor do we detect a statistically significant impact on cost and utilization during the 30 days following the index visit (although our small study samples may lack power to detect the relevant effect sizes). At least in the short run, there seem to be no adverse health effects due to the shift to remote care.

Columns 5–12 of Table 4 show results of similar analyses for the two alternative target conditions: AMI and bone fractures. We find no significant effects of remote medicine on the outcomes of diagnoses or treatment, although here too our small study samples may lack power to detect the relevant effect sizes. We nonetheless report all these results for completeness.

# 5 Heterogeneity and Robustness

## 5.1 Specification Checks

**Placebo Analysis.** To reduce concerns that our estimates capture random variation in the outcomes over time, we conduct a placebo analysis in which we reproduce our main results by estimating the model specified in equation (2) using an alternative sample that parallels our main sample, but with "placebo" pre and post periods, *both* of which had ended before widespread telemedicine adoption began. The pre period is between January 11 and February 7, 2019. The post period is between January 11 and February 7, 2020. Using this placebo sample, we estimate our main specification to compare visit outcomes of the first primary care episode for each member and period of high and low telemedicine adopters between these placebo periods. Because broad adoption of telemedicine did not yet occur by February 2020, under the identification assumptions we expect to find no difference between high and low adoption groups. Appendix Figure A4 summarizes these results. As expected, we find negligible and largely insignificant differences between outcomes associated with high adopters relative to low adopters.

**Alternative Post Period.** An important concern is that our analysis does not generalize, as during the post-lockdown period, COVID-19 still dominated the news in Israel and around the world. To explore this concern, we reproduce the main findings using an alternative post-lockdown period starting nearly a year later, from April 5, 2021 to May 30, 2021. This alternative period followed a massive vaccination campaign in Israel that had led to full suppression of COVID-19 and complete reopening of the economy. Descriptive statistics and further details on the context are discussed in Appendix D, and the results from this alternative specification are reported in Panel A of Table 5 and Appendix Figure A11.

We find that greater access to telemedicine is associated with a 3.5% increase in the share of members who have a primary care episode during the alternative post-lockdown period in 2021, which is nearly identical to the baseline estimate. Index visits of patients with high access to telemedicine involve 4.4% fewer prescriptions, which is also similar, and are not associated with an increase in referrals. The estimated impacts of 7-day physician followups (overall, with the same index physician, and in-person) maintain their sign, though their magnitude is somewhat smaller. Overall, the stability of our results is reassuring.

**Alternative Definition of Physician Adoption of Telemedicine.** To check the robustness of our results to our chosen (somewhat arbitrary) definition of telemedicine access, we reproduced all findings using an alternative measure of telemedicine adoption that considers as high and low access only patients whose physicians' estimated tendency to use telemedicine ($\alpha_j$ from equation (1)) was within the top and bottom tercile, discarding physicians from the middle tercile altogether. Key results are reported in Panel A of Table 5 and full results are reported in Appendix Figure A5 and Appendix Table A5. Results are very similar to the ones obtained using our original measure of adoption.

**Deferrability of the Index Condition.** As discussed in Section 3, an important plausible concern about our empirical strategy is that low-access patients might have been more likely to defer care during the lockdown period and consequently have greater pent-up demand for care post-lockdown.[11] Such pent-up demand would violate the parallel trends assumption (for the post period) and bias downward our estimates of the impact of telemedicine access on cost and utilization. To address this concern, we study heterogeneity in our main estimates with respect to the *deferrability* of the index condition.

To measure the deferrability of different conditions, we calculate the relative drop in overall utilization associated with each diagnosis code during the lockdown period, relative to the parallel period a year earlier. We then consider diagnoses with an above-median drop during lockdown as more deferrable and the rest as less deferrable. Appendix C provides more details on these definitions. Panel B of Table 5 shows the results of our main analysis, when estimated separately for index visits with less- and more-deferrable diagnoses.

Reassuringly, the increase in overall use of primary care due to increased access to telemedicine is concentrated in visits with diagnoses that are *less deferrable*, which should be less likely to be impacted by the concern of pent-up demand. Rather, the results are more consistent with telemedicine access driving up utilization associated with minor acute conditions. For both more- and less-deferrable visits, telemedicine access is associated with fewer prescription and referrals during the index visit and more follow-ups after it, although the decrease in the average (and total) cost of primary care episodes is concentrated in more-deferrable conditions. Appendix Figure A6 and Appendix Table A6 show results for all other outcomes. Overall, the estimated impacts of telemedicine are fairly similar between these two groups of conditions.

[11] For example, Song et al. (2021) documents a disruption to preventive care during lockdown; Ziedan et al. (2020) document a similar reduction in ambulatory and outpatient visits.

## 5.2 Heterogeneity Across Patients

Our large sample size allows us to further explore the heterogeneity in our key estimates across other different subsamples. We analyze heterogeneity of our main estimates by repeating our main analyses separately for different subsamples by age, gender, and socioeconomic status (SES). For age, we break the sample into three age groups: children (aged 0 to 18), adults (aged 19 to 64), and seniors (aged 65 and older). This split is motivated by the differences across these age groups in typical medical concerns and utilization patterns. For SES, we break the sample by terciles of an SES score defined based on the average income at the patient place of residence (see Appendix A).

These estimates for the impact of access to telemedicine on visit outcomes of different subgroups are summarized in the remaining panels of Table 5 and presented in detail in the appendix.[12] Naturally, when we focus on smaller subsamples, estimates are more noisy and statistical power is more limited. But overall, despite the differences in baseline outcomes across the different age, gender, and SES subgroups, estimates of the impact of telemedicine relative to each subgroup's own baseline are similar in magnitude. These results suggest that the estimated effects of telemedicine (or the lack thereof) are quite blunt and are not driven by any particular subgroup.

# 6 Conclusion

We analyze the impact of increased access to telemedicine using data on the universe of primary care encounters and healthcare services used by members of the largest Israeli HMO. Our empirical strategy circumvents the potential selection into either a remote or in-person setting by considering all visits (remote as well as in-person) of patients with high and low *access* to telemedicine, which we proxy based on the adoption of telemedicine by their primary care physician. This analysis makes use of the sharp—and heterogeneous—increase in telemedicine adoption during the first COVID-19 wave in Israel, which was associated with a successful mitigation of the virus and followed by a period of (temporary) return to near-normal life. We compare outcomes of patients with high and low telemedicine access in this period against the baseline, pre-COVID period.

Overall, we find that telemedicine slightly increases care utilization that is offset by a decrease in average episode intensity, resulting in overall slightly lower cost. Access to

[12]Detailed estimates for the impact of telemedicine access on visit and episode outcomes by subgroup are shown in Appendix Figure A7 (age), Appendix Figure A8 (gender), and Appendix Figure A9 (SES); estimates for the impact on total utilization and cost are shown in Appendix Table A5. Descriptive statistics for each of the subsamples are summarized in Appendix Table A7.

telemedicine has only modest impacts on outcomes of primary care visits, subsequent follow-ups, and overall utilization and cost over the 30 days following each visit. Telemedicine is associated with a modest decrease in referrals and a modest increase in follow-ups—possibly reflecting a prolonged diagnostic process due to lack of physicals. Analyzing specific conditions, we find no evidence for an increase in missed diagnoses or adverse outcomes. Given that we did not quantify multiple potential benefits of telemedicine, which include increased convenience and improved access, we consider our findings as suggesting that a combination of remote and in-person care has the potential to improve patient wellbeing.

We should emphasize some limitations to our results. First, they reflect the sorting of patient and providers into remote and in-person modes. While it appears beneficial overall, such sorting might easily change as the environment and incentives for either side change, and therefore more work would be needed to establish the impact of different factors on the success of remote provision of care. Second, our horizon is relatively short, and more work would be required to assess the longer-term consequences of shifting healthcare to remote settings on, for example, the continued interaction and nature of relationships between patients and providers. More research is clearly required to understand the many aspects of this unprecedented and universal shift of healthcare delivery, with avenues for further research including the role of supporting diagnostic technology, such as home tests or remote sensors, the design of optimal reimbursement policies, and the optimal ways to combine telemedicine and in-person care.

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Figure 1: Share of Primary Care Visits Provided Remotely

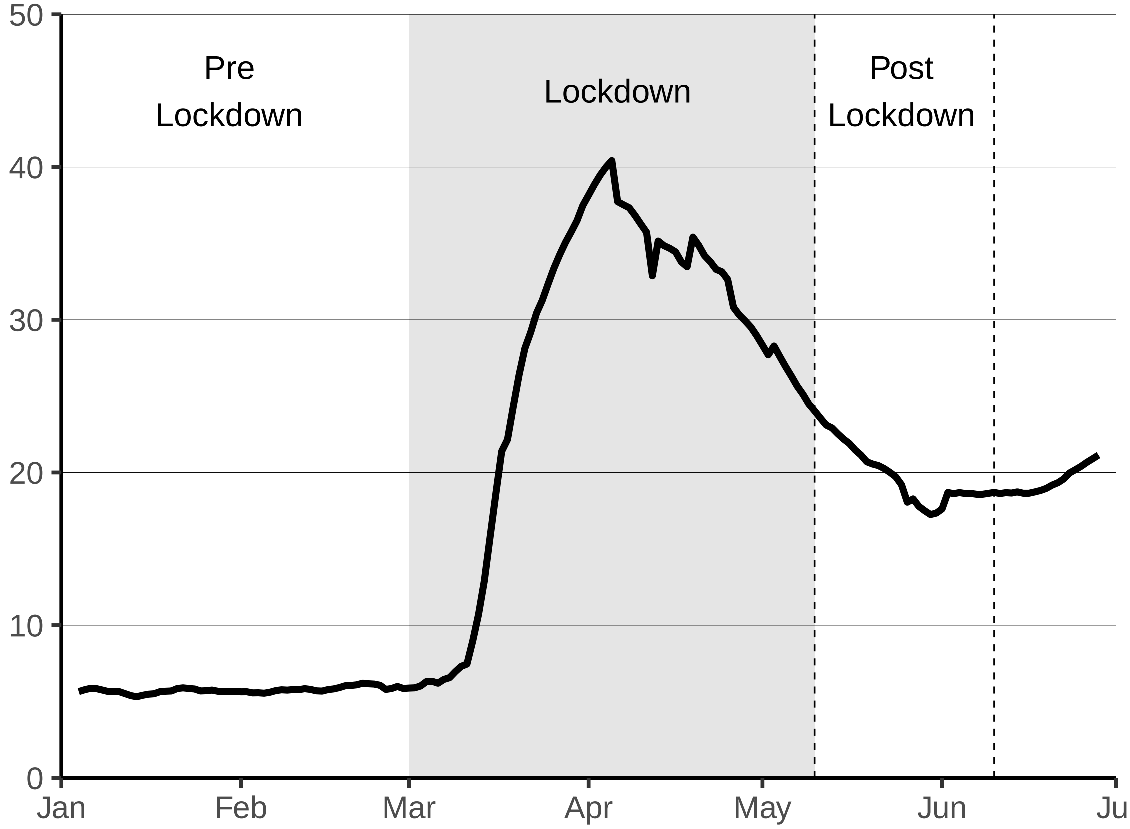



Figure shows a 7-day moving average of the daily percent of primary care visits provided remotely. Labels refer to the study periods. See Section 2.2 for detailed definitions.

Figure 2: The First COVID-19 Outbreak in Israel in 2020

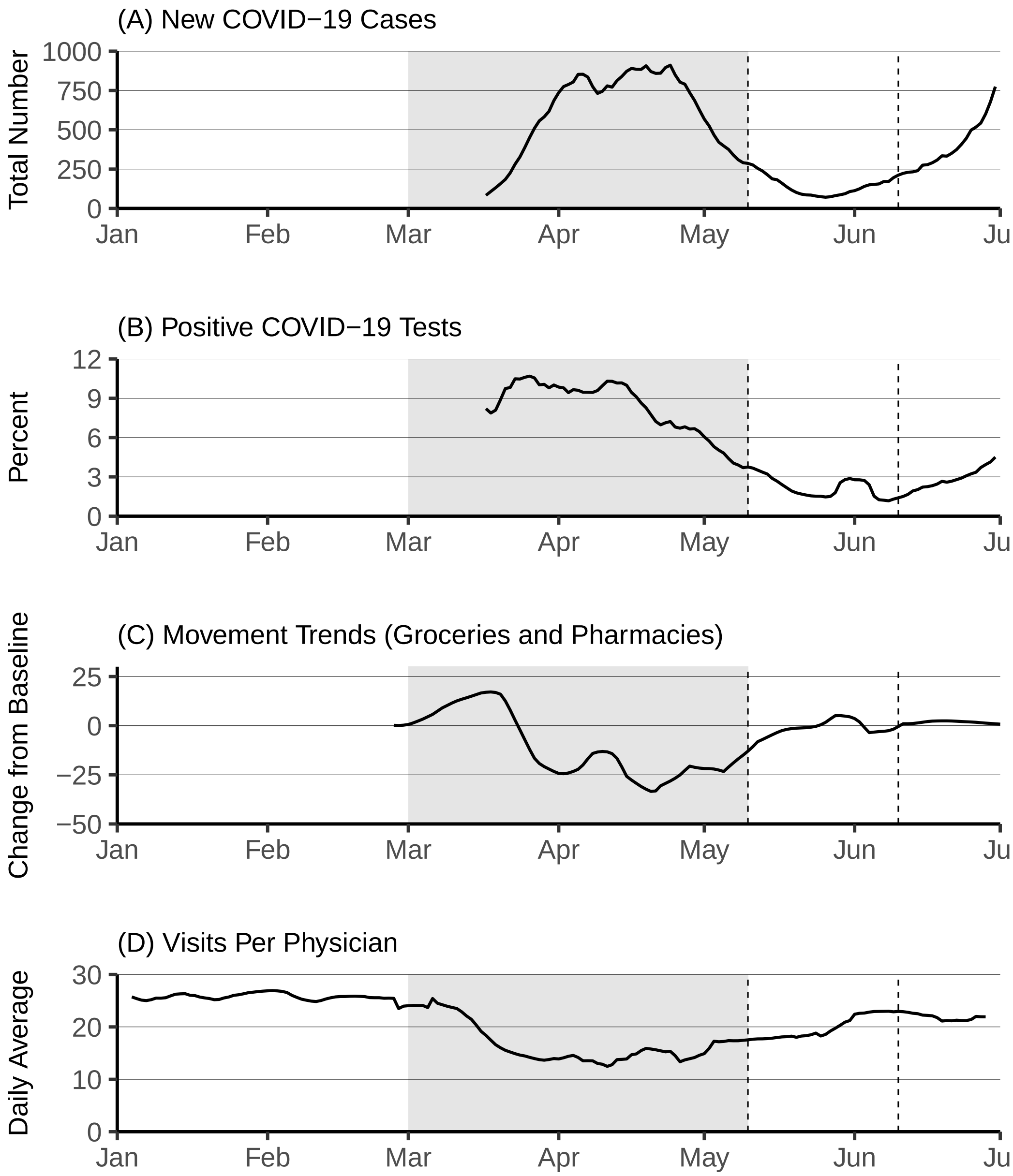
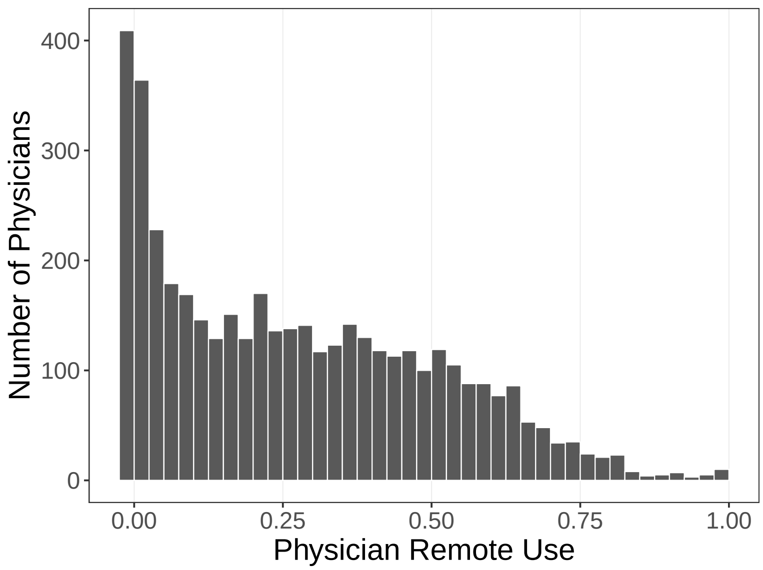



Figure shows different statistics around the time of the first COVID-19 wave in Israel in 2020. Gray-shaded areas refer to the lockdown period (March 1 to May 10) and the areas between the two vertical dashed lines refer to this study's post period (May 11 to June 7). For details, see Section 2.2. Panels A and B use data sourced from Israel's Ministry of Health and show the 7-day moving average of the daily number of new confirmed COVID-19 cases and the percent of positive tests (the hump in the percent of positive tests in May is due to low testing rates during the two-day Jewish holiday of Pentecost). Panel C uses data from Google's Global Mobility Report and shows average mobility related to groceries and pharmacies. Panel D uses data from Clalit Health Services and shows the 7-day moving average of the daily number of visits (both remote and in person) performed by primary care physicians in our study sample. All data series were smoothed using 7-day moving average. Partial series start when data are first available.

Figure 3: Physician Utilization of Telemedicine

(A) Raw Telemedicine Share of Visits




(B) Residualized Telemedicine Share of Visits

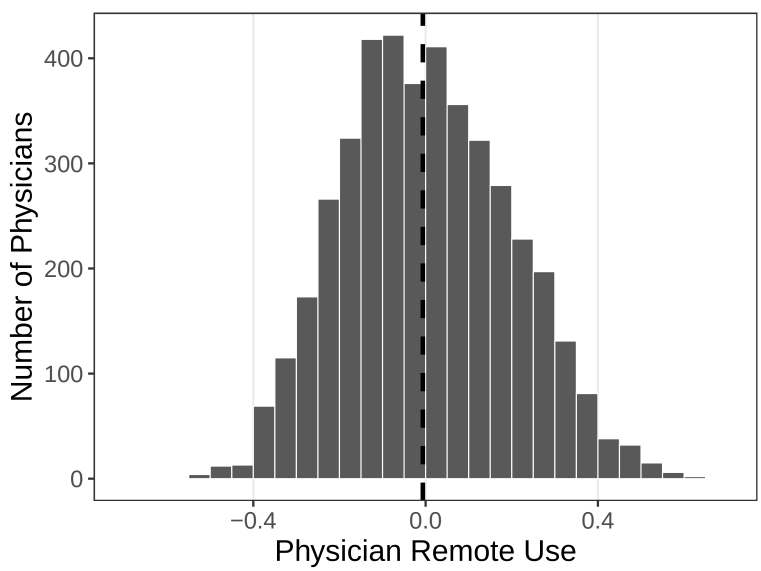



Figure shows the distribution of physician propensity to use telemedicine. Panel A shows a histogram of the share of visits that each primary care physician in our sample conducted remotely (via phone or video) during the lockdown period spanning March 1, 2020, through May 9, 2020. During this period, sampled physicians had at least 50 visits each. (The leftmost bin in this panel contains only physicians with exactly zero telemedicine visits; other bins cover left-open right-closed intervals of width 0.05.) Panel B shows the distribution of physician fixed effects estimated using equation (1) for the same set of visits as in Panel A, but controlling for case characteristics, location, and time. The vertical dashed line shows the median of this distribution ($-0.01$), which we use to classify physicians as high or low adopters.

Figure 4: Flexibly Estimated Time Trends in Common Visit Outcomes, by Physician Telemedicine Use During the Lockdown Period

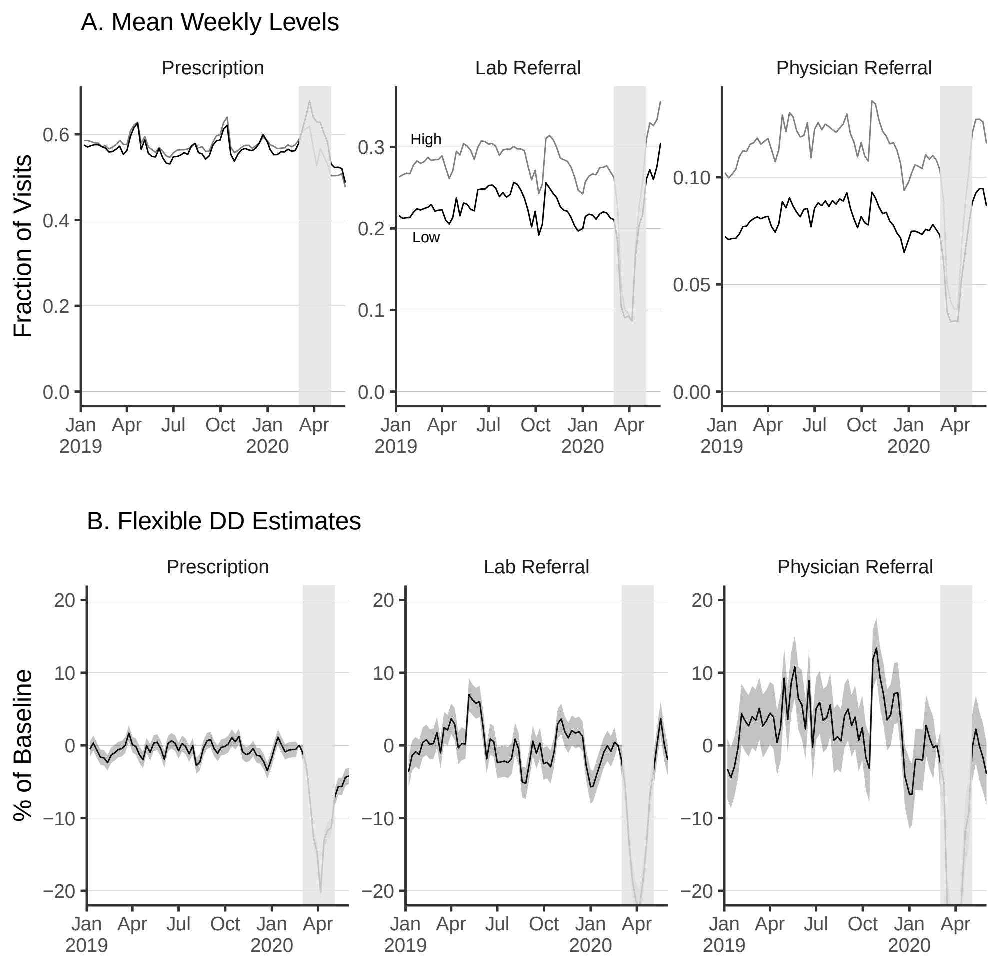



Figure shows, using the sample of all visits starting new primary care episodes, flexibly estimated time trends for the three most common visit outcomes. Panel A shows raw (unadjusted) weekly means for visits of patients affiliated with high telemedicine adopters (High) and low telemedicine adopters (Low). Panel B shows flexible difference-in-differences estimates of the impact of high access to telemedicine from a version of equation (2) with the same fixed effects and controls but with fully flexible week dummies (and the same week dummies interacted with a dummy for High). The figure shows the estimates of week dummies interacted with dummy for High relative to the (omitted) last week of the pre-lockdown period. The 95% confidence interval is shown in dark gray. For comparability, estimates and their confidence intervals are expressed as a share (percent) of each mean outcome in the pre-lockdown period. The shaded light gray rectangles mark the lockdown period, which we only use for the measurement of telemedicine adoption but otherwise exclude from the analyses. Outcomes are not mutually exclusive. See Section 2.2 for detailed variable definitions.

Figure 5: The Impact of Increased Access to Telemedicine on Index Visit In-Visit Actions and 7-Day Follow-Ups

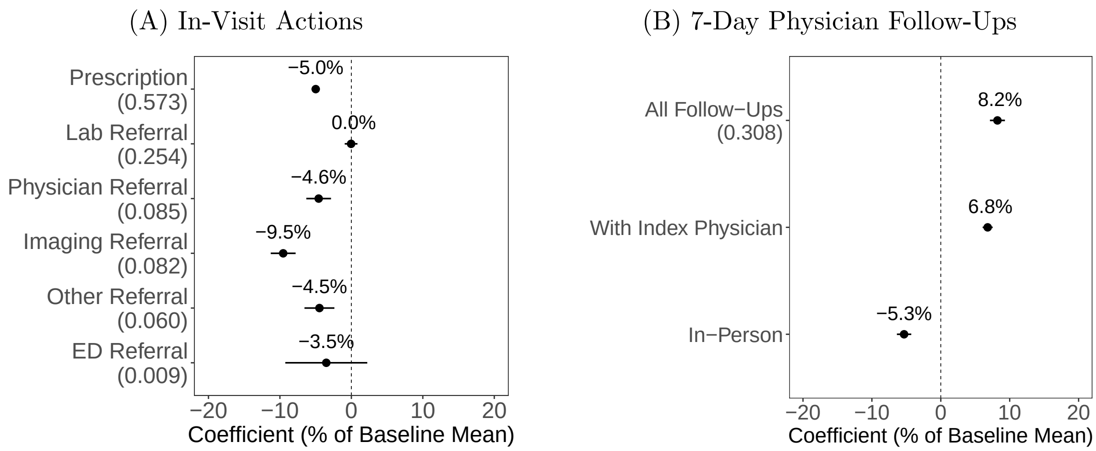



Figure shows the estimated impacts of increased access to telemedicine on visit outcomes. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine ($\beta$ from equation (2)) for a different outcome. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period (shown in parenthesis). In Panel B, all coefficients are represented as a percent of the mean of all follow-ups (0.308). Appendix Table A8 (Panels A and B) shows the unscaled estimates. The sample includes all new primary care episodes that took place in the pre-lockdown period of January 2019–February 2020 and the post-lockdown period of May–June 2020. Outcomes shown are for the first visit of each episode. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Section 2.2 discusses in more detail the sample and variable definitions.

Figure 6: The Impact of Increased Access to Telemedicine on Cost and Utilization 30-Days After an Index Primary Care Visit

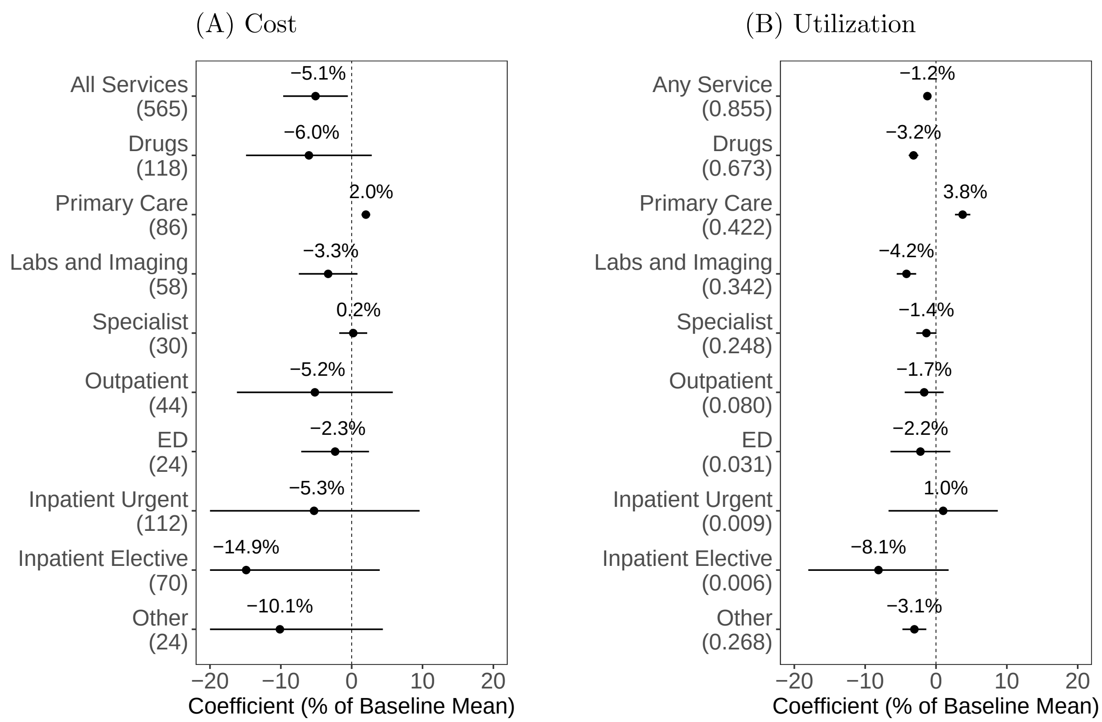



Figure shows the estimated impacts of increased access to telemedicine on cost and utilization.. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine ($\beta$ from equation (2)) for a different outcome. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period (shown in parenthesis). Panel A shows estimates for the average cost of services, by type of service. Costs are inclusive of the index visit; remote and in-person visits were reimbursed at the same rate during the study period. Panel B shows estimates for the probability of use of each service. Primary care utilization refers to additional visits (excluding the index visit). Appendix Table A8 (Panels C and D) shows the unscaled estimates. Outcomes are sorted by their pre-lockdown mean. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 2.2 discusses in more detail the sample and variable definitions.

Table 1: Patient, Visit, and Episode Characteristics, by Index Visit Setting

| | **In-Person** (1) | **Remote** (2) |
|---|---|---|
| **A. Patient Characteristics** | | |
| Female | 0.541 | 0.582 |
| High SES | 0.262 | 0.417 |
| Age | 36.8 | 40.2 |
| ACG | 1.032 | 1.159 |
| Number of Chronic Conditions | 2.564 | 2.949 |
| **B. In-Visit Actions** | | |
| Prescription | 0.531 | 0.382 |
| Lab Referral | 0.309 | 0.324 |
| Physician Referral | 0.098 | 0.079 |
| Imaging Referral | 0.093 | 0.062 |
| Other Referral | 0.066 | 0.060 |
| ED Referral | 0.008 | 0.005 |
| **C. Number of 7-Day Physician Follow-Ups** | | |
| All Follow-Ups | 0.333 | 0.378 |
| With Index Physician | 0.165 | 0.204 |
| Not With Index Physician | 0.167 | 0.174 |
| Remote | 0.041 | 0.134 |
| In-Person | 0.292 | 0.245 |
| **D. 30-Day Cost (NIS)** | | |
| All Services | 657 | 688 |
| Drugs | 129 | 155 |
| Inpatient Urgent | 130 | 138 |
| Primary Care | 89 | 92 |
| Inpatient Elective | 93 | 76 |
| Labs and Imaging | 73 | 78 |
| Outpatient | 55 | 56 |
| Specialist | 35 | 38 |
| ED | 23 | 21 |
| Other | 31 | 33 |
| Number of Visits | 453,966 | 101,671 |

Table compares mean outcomes between telemedicine visits and in-person visits that start new care episodes. The sample includes the post-lockdown period; its construction is discussed in Section 2.2. Costs are in current New Israeli Shekels (NIS). Outcomes in Panel B are indicators for each outcome occurring during the index visit. In Panel C, Number of 7-Day Phyisician Follow-Ups is the number of physician visits made by the patient in the 7 days following the index visit, with both primary care physicians and specialists. In Panel D, 30-Day Cost include the cost of all events that started within 30 days of an index primary care visit.

Table 2: Physician and Case Characteristics, by Physician Telemedicine Adoption Status

| | **High** (1) | **Low** (2) |
|---|---|---|
| **A. Physician Characteristics** | | |
| Age | 51.6 | 54.5 |
| Female | 0.589 | 0.312 |
| Pediatrician | 0.201 | 0.306 |
| Weekly Visits | 89.9 | 96.7 |
| Share Remote | 0.319 | 0.061 |
| Number of Physicians | 2,146 | 2,147 |
| **B. Case Characteristics (Affiliated Patients)** | | |
| Age | 40.7 | 34.7 |
| Female | 0.559 | 0.539 |
| High SES | 0.373 | 0.223 |
| ACG | 1.16 | 0.97 |
| Number of Chronic Conditions | 2.97 | 2.36 |
| Share Remote | 0.303 | 0.083 |
| Number of Visits | 251,434 | 304,203 |

Table shows characteristics of physicians and their patient case mix during the post-lockdown period, by physician propensity to adopt telemedicine. To measure physician adoption, we estimate, using the model equation (1), each physician's tendency to shift care remotely during the COVID-19 lockdown period (of March-April 2020), adjusting for case mix, time, and place. Based on this analysis, we consider physicians whose adoption was above median as high adopters (High) and the rest as low adopters (Low). The two column show data separately for these groups of physicians. Panel A shows the characteristics of physicians in each group. Panel B shows summary statistics for the visits of patients affiliated with physicians in each group in the post-lockdown period. The sample used in Panel B includes non-follow-up primary care visits with any primary care physician, not just the main primary care provider. See Section 2.2 for detailed definitions.

Table 3: The Impact of Telemedicine on Utilization and Total Cost of Care

| | Pre-Lockdown Mean | Estimated Impact | (S.E.) | Percentage Impact |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A. Utilization** | | | | |
| Any Healthcare Utilization | 0.511 | 0.0014 | (0.0007) | 0.3% |
| Any Primary Care Episodes | 0.178 | 0.0063 | (0.0005) | 3.5% |
| **B. Cost (NIS)** | | | | |
| Total Healthcare Cost | 463 | -14 | (7) | -3.0% |
| Total Cost of Primary Care Episodes | 105 | -6 | (2) | -5.7% |

The table shows the estimated impacts of increased access to telemedicine on utilization and total cost of care. Each row shows an estimate of $\beta$ from equation (2) for a different outcome. Utilization is defined as the share (between 0 and 1) with any service use. Cost is defined as the total cost of services used. The sample includes all members, including those with zero utilization. Primary care episodes refer to care episodes starting with a primary care visit that had no other encounters in the 14 days preceding it. Total cost of new primary care episodes includes all services utilized within 30 days of the index visit data.

Table 4: The Impact of Telemedicine on the Diagnosis of Specific Medical Conditions

| | UTI | | | | AMI | | | | Fractures | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean (1) | Estimate (2) | (S.E.) (3) | Percent (4) | Mean (5) | Estimate (6) | (S.E.) (7) | Percent (8) | Mean (9) | Estimate (10) | (S.E.) (11) | Percent (12) |
| **A. Diagnosis Rates** | | | | | | | | | | | | |
| Target Condition dx (Index) | 0.403 | 0.008 | (0.020) | 2.0% | 0.023 | 0.002 | (0.011) | 9.4% | 0.385 | 0.009 | (0.038) | 2.4% |
| Target Condition dx (Episode) | 0.434 | 0.010 | (0.020) | 2.3% | 0.026 | 0.007 | (0.012) | 25.4% | 0.393 | 0.003 | (0.039) | 0.8% |
| Number of Recorded dx Codes | 1.600 | -0.084 | (0.044) | -5.3% | 2.100 | 0.023 | (0.085) | 1.1% | 1.880 | 0.013 | (0.116) | 0.7% |
| Share of Recorded Codes that Represent Symptoms | 0.444 | 0.008 | (0.020) | 1.9% | 0.509 | 0.049 | (0.030) | 9.6% | 0.560 | -0.033 | (0.036) | -5.9% |
| **B. Diagnostic Tests** | | | | | | | | | | | | |
| Test Referral (Index) | 0.408 | 0.041 | (0.023) | 10.1% | 0.012 | 0.008 | (0.008) | 70.4% | 0.132 | 0.035 | (0.029) | 26.4% |
| Test Performance (Episode) | 0.380 | 0.035 | (0.023) | 9.3% | 0.010 | 0.004 | (0.008) | 40.5% | 0.144 | 0.035 | (0.031) | 24.4% |
| Test Positivity (Episode) | 0.075 | 0.002 | (0.012) | 2.1% | | | | | | | | |
| **C. Prescriptions** | | | | | | | | | | | | |
| Prescriptions (Index) | 0.206 | 0.008 | (0.018) | 4.0% | 0.053 | 0.006 | (0.016) | 11.7% | 0.082 | -0.055 | (0.025) | -67.7% |
| Prescriptions (Episode) | 0.253 | 0.010 | (0.019) | 4.1% | 0.118 | 0.017 | (0.022) | 14.1% | 0.120 | -0.047 | (0.029) | -39.2% |
| **D. 7-Day Physician Follow-Ups** | | | | | | | | | | | | |
| All | 0.559 | 0.015 | (0.073) | 2.6% | 0.667 | -0.086 | (0.115) | -12.9% | 0.610 | 0.038 | (0.143) | 6.3% |
| With Index Physician | 0.258 | 0.051 | (0.050) | 19.9% | 0.292 | 0.036 | (0.079) | 12.4% | 0.240 | 0.143 | (0.104) | 59.5% |
| Remote | 0.045 | 0.060 | (0.023) | 132.5% | 0.035 | 0.102 | (0.036) | 292.7% | 0.023 | 0.019 | (0.040) | 83.0% |
| **E. Utilization and Cost** | | | | | | | | | | | | |
| Specialist Referral (Index) | 0.113 | -0.008 | (0.014) | -7.0% | 0.121 | 0.001 | (0.024) | 0.6% | 0.118 | 0.003 | (0.028) | 2.9% |
| ED Referral (Index) | 0.014 | -0.001 | (0.006) | -5.3% | 0.051 | 0.014 | (0.015) | 27.7% | 0.040 | -0.005 | (0.017) | -13.6% |
| ED Use (24 Hours) | 0.007 | 0.001 | (0.004) | 10.4% | 0.012 | 0.003 | (0.008) | 21.5% | 0.009 | -0.018 | (0.009) | -196.9% |
| ED Use (Episode) | 0.053 | 0.004 | (0.011) | 8.3% | 0.072 | -0.034 | (0.018) | -47.5% | 0.051 | -0.019 | (0.020) | -37.8% |
| UCC Use (Episode) | 0.020 | -0.008 | (0.007) | -38.4% | 0.041 | -0.012 | (0.013) | -30.4% | 0.046 | -0.014 | (0.018) | -30.5% |
| Total Cost (Episode) | 737 | 176 | (172) | 23.8% | 1060 | -456 | (325) | -43.0% | 647 | -153 | (349) | -23.6% |

Table shows estimates of the impact of access to telemedicine ($\beta$ from the model specified in equation (2)), for subsamples of specific conditions and their differential diagnoses. The samples are described in detail in Section 4.3. Different rows show results for different outcomes. For each condition, the first column shows the pre-lockdown mean outcome, the second and third columns show the (unscaled) estimate and standard error of the impact of access to telemedicine on the outcome, and the fourth column shows the estimate as a percent of the pre-lockdown mean. Diagnostic tests refer to urine test for UTI, electrocardiogram (ECG) for AMI, and X-ray for fractures. Prescriptions refer to specific antibiotics for UTI, aspirin and nitroglycerin for AMI, and opioids for fractures. Section 4.3 and Appendix B describe the sample construction, variable definitions, and empirical specifications in detail.

Table 5: Robustness and Heterogeneity

| | Index Visit and Episode Outcomes | | | | | Overall Cost and Use of Primary Care Episodes | |
|---|---|---|---|---|---|---|---|
| | Prescrip-tion | Lab Referral | 7-Day Follow-Ups | 30-Day Cost | 30-Day Utilization | Overall Cost | Overall Use |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **A. Specification** | | | | | | | |
| Main Specification | -5.0% | 0.0% | 8.2% | -5.1% | -1.2% | -5.7% | 3.5% |
| | (0.2%) | (0.5%) | (0.6%) | (2.3%) | (0.2%) | (1.9%) | (0.3%) |
| Alternative Access Measure | -6.1% | -0.1% | 11.0% | -3.2% | -1.2% | -5.6% | 5.5% |
| | (0.5%) | (1.1%) | (0.9%) | (2.7%) | (0.2%) | (2.8%) | (0.3%) |
| Alternative Post Period | -4.4% | -1.1% | 2.4% | | | | 3.5% |
| | (0.4%) | (0.7%) | (0.7%) | | | | (0.2%) |
| **B. Deferrability** | | | | | | | |
| More Deferrable | -4.3% | -1.1% | 9.4% | -6.1% | -1.0% | -9.7% | -0.2% |
| | (0.4%) | (0.9%) | (0.9%) | (2.7%) | (0.2%) | (2.8%) | (0.4%) |
| Less Deferrable | -5.7% | 4.8% | 6.1% | -1.3% | -1.4% | 3.1% | 9.7% |
| | (0.6%) | (1.5%) | (1.3%) | (4.4%) | (0.3%) | (3.1%) | (0.5%) |
| **C. Age Group** | | | | | | | |
| Child (0-18) | -3.2% | -7.1% | 10.9% | -9.6% | -1.2% | -3.4% | 1.2% |
| | (0.7%) | (1.9%) | (1.7%) | (4.8%) | (0.4%) | (5.2%) | (0.5%) |
| Adult (19-64) | -7.0% | -0.4% | 7.1% | -8.9% | -1.8% | -9.3% | 0.1% |
| | (0.5%) | (1.0%) | (1.0%) | (3.4%) | (0.2%) | (3.1%) | (0.4%) |
| Senior (65+) | -2.5% | 1.7% | 6.3% | 0.1% | -0.1% | -6.1% | -3.8% |
| | (0.5%) | (1.2%) | (1.4%) | (4.1%) | (0.2%) | (3.6%) | (0.8%) |
| **D. Gender** | | | | | | | |
| Male | -4.2% | -0.2% | 9.3% | -4.4% | -0.9% | -7.5% | 3.4% |
| | (0.5%) | (1.1%) | (1.1%) | (3.8%) | (0.3%) | (3.7%) | (0.4%) |
| Female | -5.7% | 0.1% | 7.3% | -5.8% | -1.5% | -3.7% | 3.6% |
| | (0.4%) | (0.9%) | (0.9%) | (2.8%) | (0.2%) | (2.8%) | (0.4%) |
| **E. SES** | | | | | | | |
| Low | -3.0% | 0.8% | 3.8% | -15.4% | -1.1% | -14.4% | -1.5% |
| | (0.7%) | (1.7%) | (1.5%) | (4.8%) | (0.3%) | (5.2%) | (0.6%) |
| Medium | -3.8% | -2.6% | 8.7% | 4.6% | -0.8% | 6.8% | 7.7% |
| | (0.5%) | (1.3%) | (1.2%) | (3.6%) | (0.3%) | (3.4%) | (0.5%) |
| High | -4.1% | -3.3% | 8.3% | -3.5% | -0.6% | -0.9% | 7.2% |
| | (0.6%) | (1.2%) | (1.3%) | (4.2%) | (0.3%) | (3.6%) | (0.5%) |

Table shows estimates and standard errors (in parentheses) of the impact of access to telemedicine ($\beta$ from the model specified in equation (2)) for different key outcome (in columns) and for different specifications (in rows). Estimates are scaled as a percent of each outcome's pre-lockdown mean. Each panel summarizes the results for a different analysis, as follows: Panel A compares the study's main specification with a specification using an alternative measure of telemedicine access, based on comparing top and bottom terciles of utilizers, rather than above- and below-median utilizers. The sample consists of all primary care episodes of patients affiliated with primary care doctors in the top and bottom terciles of telemedicine utilization during the lockdown period. Panel B repeats our main analyses using the main study sample, separately for outcomes of visits that are more or less deferrable. Panels C–E repeat our main analyses separately for different subsamples defined by age group, gender, and tercile of socioeconomic rank (defined based on the average income at the patient place of residence). Section 5 and Appendix A discuss in detail the specifications and definitions. Appendix Table A7 shows descriptive statistics for each of the subsamples.

# Appendix A Sample and Variable Definitions

## A.1 Construction of the Main Sample

Our main sample consists of all primary care episodes of patients that were affiliated with active primary care physicians. This section describes the sample construction, which involved three main steps: (i) sample all active primary care physicians, (ii) sample all their affiliated patients, (iii) sample all episodes for these patients.

**Active Physicians.** We sampled all Clalit physicians who serve as primary care providers; specifically, family physicians and pediatricians. We then sampled all remote and in-person primary care visits conducted by these primary care providers between January 7, 2019, and June 7, 2020 (these physicians are salaried by—and work exclusively for—Clalit, so we observe their universe of patient encounters). We included in the sample only *active* physicians, defined as physicians who performed at least 50 visits in the lockdown period (an average physician sees more patients within a single week). This resulted in the exclusion of a small number of inactive physicians that account for less than 1% of all visits. This sample has 4,293 active primary care physicians.

**Physician-Patient Affiliation.** We sampled all patients affiliated with any one of these 4,293 active physicians. We consider a physician to be the main primary care provider of a patient if the patient saw this physician the most times in the pre-lockdown period (January 2019 through February 2020).[13] If the patient visited multiple doctors the same (maximal) number of times, we pick as the primary provider the physician whom the patient saw last during that period. We exclude from the sample 10% of Clalit members who had no physician visits throughout the pre-lockdown period, for whom affiliation thus defined is indeterminate. These excluded members account for only 2% of total baseline cost of services. This sample has 4.313 million patients.

**Primary Care Episodes.** For each sampled patient, we extract all primary care visits that occurred during the study period of January 7, 2019, to June 7, 2020, either in person or remotely. Our focus is new primary care episodes, so we exclude visits that had any encounters with physicians, hospitals, or labs during the 14-day period preceding the visit because such visits likely reflect follow-up encounters that are part of an ongoing episode. The remaining non-follow-up visits account for 44% of all visits. We refer to each one of

[13] Clalit maintains a large network of salaried primary care physicians. Patients in Clalit are free to visit any in-network physician, but they are encouraged to stick to one physician for managing their care.

these (new) visits as the *index* visit of a care episode and attribute all services utilized in the 30-day period subsequent to this index visit to this episode. For consistency across our different analyses, we include in our main sample only episodes that had non-missing control variables (the list of which is described below), resulting in the exclusion of a small number of observations that missed one or more covariates. The resulting sample consists of 12.198 million primary care episodes involving 3.655 million unique patients. This excludes 0.4 million members who, during the study period, did not have any new primary care episodes.

**Study Periods.** We split our main sample into three periods based on the timeline of the COVID-19 outbreak and mitigation measures in Israel. All periods begin on a Monday and their lengths are multiples of 7 days. First is the *pre-lockdown* period, between January 7, 2019 (the first Monday of 2019) and March 1, 2020, when the first COVID-19 case was identified in Israel. Second is the *lockdown* period between March 2, 2020, and May 10, 2020, when lockdown restrictions easing went into effect. Third is the *post-lockdown* period of relative normalcy between May 11, 2020, and June 7, 2020, when the number of daily cases started climbing again. We assign each primary care episode to a study period based on the date of the index visit.

## A.2 Construction of Additional Samples

**Sample Used for Studying Total Healthcare Cost and Utilization.** To estimate the impact of telemedicine access on *overall* care utilization, we sample, for the 4.313 million patients for whom we have determined a physician affiliation, all healthcare utilization that occurred between May 11 and June 7, 2019, (an alternative, shorter pre-lockdown period) and between May 11 and June 7, 2020 (the same post period as in the main sample). We restricted this sample to cover a shorter baseline (pre-COVID) period because extracting detailed cost data for the entire member population over extended periods of time is computationally demanding. We selected the timing of this shorter sampled pre period to match exactly the time of year of the post period to minimize the scope for differences between the periods that are related to seasonality in healthcare use.

For these same patients and periods, we also measure cost and use directly associated with primary care episodes, as defined in Appendix Section A.3. The resulting sample covers 1.178 million episodes involving 1.067 million unique patients.

## A.3 Variable Definitions

**Utilization and Total Cost.** We observe payments for all services detailed in encounter-level claims data (including inpatient admissions, emergency department visits, treatments and diagnostic services provided in outpatient clinics, both within and outside hospitals, and prescription drug purchases). The spending measures represent actual payments made by Clalit, not list charges. Even hospitals owned by Clalit are separate financial entities, as they serve both Clalit and non-Clalit patients, so hospital charges in all case reflect actual payments, not transfer prices. The only exception is office-based consults provided by physicians in Clalit-owned clinics, for which there is no actual charge, as physicians are salaried. For these visits, we (and Clalit) impute per-visit charges based on customary charges by non-employed providers. During the period of our study, these charges were the same for in-person and remote visits. Our total cost measure is computed by adding up, for each patient, the costs of all healthcare activities during the relevant period. Our overall utilization outcome is an indicator variable that assumes the value of 1 if the patient utilized any service during the period, and 0 otherwise.

Our measures of utilization and total cost over an entire period include all events that started during the period, regardless of when they ended. Our measures of overall utilization and cost associated with primary care episodes during a period include all events that started within 30 days of an index primary care visit (including the index visit itself), regardless of when they ended. We never double-count costs: in a small number of cases when there are overlapping primary care episodes within the same period (namely, two episodes with index visits that are more than 14 days but less than 30 days apart), our measure for the overall cost of primary care episodes during the period is the sum of the cost of all events that started between the index date of the first episode through 30 days after the index date of the last episode.

We also observe cost and use separately for each of the following service categories: prescription drug purchases, primary care physician visits (remote and in-person), specialist visits, lab tests and imaging procedures, visits to outpatient facilities, emergency department visits (ED), inpatient admissions through the ED (inpatient urgent), inpatient admissions not through the ED (inpatient elective), and all other covered services.

**Visit and Follow-Up Outcomes.** For each primary care visit, we observe the diagnosis codes entered by the physician in the visit summary, drugs that were prescribed by the physician to the patient on the date of the visit (regardless of whether the prescription was ever filled by the patient), and referrals made on the date of the visit to each of the following providers: physician specialists and surgeons; imaging, including X-ray, ultrasound, computed tomography (CT) scans, electrocardiogram (ECG), mammogram, electromyography (EMG), and magnetic resonance imaging (MRI); and emergency department (ED). We group all other non-physician referral targets, the most common of which are physical therapists and dietitians, under the label Other.

To determine the 7-day follow-up outcomes, we calculate the number of physician visits made by the patient in the 7 days following the index visit, with both primary care physicians and specialists. We separately count follow-up visits by whether they were with the same physician who handled the index visit or with other physicians and separately, by the follow-up visit setting: remote or in-person.

**Control Variables.** We use the following variables as visit-level controls: patient gender, patient age, Johns Hopkins Adjusted Clinical Group concurrent weight, number of diagnosed chronic conditions, the visit location (subdistrict), and category of diagnosis. This section describes these variables in detail.

The patient age is the patient five-year age group at the time of the visit. ACG concurrent weight is a risk score that is calculated on a quarterly basis using a commercial classifier.[14] We exclude 2% of episodes with missing ACG scores. Chronic condition counts are based on indicators for 123 chronic condition obtained from a database maintained by Clalit. The ten most common conditions are hyperlipidemia, smoking (as documented in EMR; smoking is a health behavior that is predictive of future healthcare utilization and spending and is thus treated for this purpose like a chronic condition), hypertension, obesity, arthropathy, diabetes, malignancy, ischemic heart disease, arrhythmia, and asthma. The visit location is observed at the level of subdistrict, an administrative division of Israel into 70 geographic areas, each with a similar number of covered members. To determine the diagnostic category of a visit, we group the first diagnosis code of each visit into one of the following 16 diagnosis categories: mental health; endocrine, immune, or lymphatic; urinary/renal; reproductive; brain/neurological; dental; administrative; heart and blood Vessels; digestive; respiratory; muscles and skeleton; ear, nose, and throat; eyes; skin; injury/wound/trauma; and other. The association between diagnoses and categories was determined by uploading the English description of the 500 most common diagnoses, which together cover over 90% of cases in our sample, to multiple Amazon Mechanical Turk workers who were asked to classify them, based on Google searches, to the most appropriate category. In case of a disagreement, the most commonly selected category was assigned. We exclude the 8.5% of cases with no associated diagnostic category.

In descriptive analysis and when analyzing heterogeneity, we also use the patient socioeconomic status (SES). SES is calculated based on the Israel Central Bureau of Statistics

[14] ACG is a risk-scoring system that is used by both commercial insurers and non-commercial healthcare organizations worldwide (as well as by Clalit) to describe or predict a population's past or future healthcare utilization and costs. For more information, see the Johns Hopkins ACG System Version 11.0 Technical Reference Guide (2014).

socioeconomic classification of the patient municipality of residence. These classifications are based on national income tax records.

# Appendix B Sample and Variables Used for Analyzing Diagnostic Accuracy

## Sample Construction

To evaluate the impact of telemedicine on diagnostic accuracy, we analyze the diagnostic process of three medical conditions: urinary tract infection (UTI), acute myocardial infarction (AMI), and bone fracture. UTI is an infection in any part of the urinary system—kidneys, ureters, bladder, or urethra. Most infections involve the lower urinary tract—the bladder and the urethra. An infection limited to the bladder can be (just) painful and annoying, whereas a UTI that spreads to the kidneys can result in serious complications. A urine test is commonly used to diagnose of a UTI. Antibiotics are usually the first line treatment.[15] AMI, a potentially fatal condition, occurs when the flow of blood to the heart is blocked. Although some heart attacks strike suddenly, many people have warning signs and symptoms hours, days, or weeks in advance, and some people who have heart attacks have only mild symptoms. The first diagnostic test for AMI is an electrocardiogram (ECG).[16] Fractures—broken bones—are caused mainly by trauma or osteoporosis (a disorder that involves a reduction in bone density) and are commonly diagnosed using X-ray imaging. Common treatments for fractures include immobilization and pain management.

To account for the endogeneity of the diagnosis itself—particularly, for the possibility that physicians may be less accurate in remote settings—we sample each target condition with all related conditions that share similar symptoms and are therefore part of its differential diagnosis. In consultation with a Clalit physician with clinical experience in family medicine, we created a list of all differential diagnoses associated with each target condition. Appendix Table A1, Appendix Table A2, and Appendix Table A3 show the respective lists of target and differential diagnoses that were used in the construction of each sample. For brevity, we refer to these samples by the name of the target condition (e.g., the UTI sample refers to the sample of UTI and all related differential diagnoses).

For each set of target condition and related differential diagnoses, we sampled all non-follow-up primary care visits that occurred between May 11, 2019, and June 7, 2019, and

[15]Source: Urinary Tract Infection - Diagnosis and Treatment - Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/urinary-tract-infection/diagnosis-treatment/drc-20353453. Accessed March 2021.

[16]Source: Heart Attack - Diagnosis and Treatment - Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/heart-attack/diagnosis-treatment/drc-20373112.

between May 11, 2020, and June 7, 2020 for which the physician recorded at least one of the diagnoses in the visit summary. If members had multiple such visits in the pre or post period, we only consider the member's first visit in each period. We include only physicians who conducted at least one in-person and one remote visit during the post period. Our resulting samples have 14,800 observations for UTI, 10,100 observations for AMI, and 8,500 observations for fractures. Appendix Table A4 shows detailed summary statistics that specify all risk factors, diagnostics, and outcomes we use for each of the subsamples, which are discussed in detail in the next section.

## Condition-Specific Variables

When focusing on specific medical conditions, in addition to (and sometimes in place of) the controls we used in our main analyses, we include controls for risk factors and outcomes that are specific to each target condition. This section describes these variables in detail.

**Risk Factors.** Controls specific to the UTI sample include an indicator for any UTI diagnosis in the last year and the quantile (1–5) of number of months in the last year with a UTI diagnosis. Controls specific to the AMI sample include an indicator for whether the member is identified as currently smoking, an indicator for whether he has received any prescription for antihypertensive drugs since 2010, the last recorded systolic blood pressure reading, the last recorded total cholesterol value, the last recorded high-density lipoprotein (HDL) cholesterol value, and an indicator for a past diagnosis of diabetes. Controls specific to the fractures sample include an indicator for a current diagnosis of osteoporosis and four indicators for the part of the body to which the diagnosis relates (head, leg, arm, and torso).

**Coding of Diagnostic Codes.** In order to assess the diagnostic certainty of physicians, we consider two outcomes related to the visits' associated diagnosis codes: the number of diagnosis codes recorded for each index visit and the share of these diagnoses that represent symptoms, as opposed to true diagnoses or administrative or medical procedures. To calculate these, we took the full set of diagnoses from the visits in each sample and categorized the top 150–200 diagnoses, depending on the sample, as symptoms, diagnoses, administrative procedures, or medical procedures. Our categorization covers 75–85% of diagnosis codes for visits in each of the samples. The total number of diagnosis codes is the number of categorized diagnosis codes in the visit. The symptom share is calculated by dividing the number of codes categorized as symptoms divided by the total number of categorized codes.

**Diagnosis Rates.** We observe the rates of diagnosis of each of the target conditions, based on ICD9 codes recorded in visit summaries. Target diagnosis codes for each sample are listed in Panel A of Appendix Table A1, Appendix Table A2, and Appendix Table A3. We separately measure diagnosis rates during index visits and during the entire episode. We consider a diagnosis to have occurred during a visit if at least one target ICD9 was recorded. We consider a diagnosis to have occurred during an episode if it occurred during any encounter with a physician in a community setting (remotely or in-person) that took place over the 30-day period starting on the date of the index visit, including the index visit itself.

**Diagnostic Procedures.** We observe the following condition-specific diagnostic procedures: for UTI, a urine culture (urine test); for AMI, an electrocardiogram (ECG); for fractures, an X-ray. We measure both referral rates to these tests during the index visit and performance rates of the procedures over the 30-day period starting with the index visit. For urine cultures performed during the episode, we also observe the test outcome, namely, whether the culture was positive for significant microbial growth, defined as 100,000 colony forming unites (CFUs) per milliliter, the accepted threshold.

**Prescription Drugs.** We observe the following prescriptions that are related to the target conditions: antibiotics that are used for the treatment of UTI, aspirin and nitroglycerin for AMI, and any opioid prescription for fractures. We measure index-visit prescriptions as prescriptions made by the index physician on the index date. We measure episode-related prescriptions as prescriptions made by any physician during the 30 days starting with the index date. We date prescriptions to the time they are prescribed by a physician, regardless of whether and when they are filled by the patient.

**Other Outcomes.** For all samples, we consider the same 7-day follow-up outcomes we used in our main analysis. We also considered the following outcomes: an indicator for a referral to the emergency department in the index visit, an indicator for visiting the ED on the index date or the day after, an indicator for visiting the emergency department on the index date or 30 days following the index date, an indicator for visiting an urgent care center (UCC) on the index date or the 30 days following the index date, and the total cost of healthcare services utilized during the 30-day period starting with the index visit.

# Appendix C Sample and Variables Used for Analyzing Deferrability

To analyze the deferrability of index visits, we sample all non-follow-up primary care visits that occurred between March 2 and May 10, 2020 (the same lockdown period as in the main sample) and March 2 and May 10, 2019 (the same period in the previous year). We then sample all ICD9 diagnosis codes that appeared on these visits' summaries, excluding the 1% least-common diagnosis codes (each of which appeared fewer than 100 times in either 2019 or 2020). For each diagnosis code, we calculate a deferrability score, defined as the ratio of the number of visits with this code in the 2020 and 2019 sample periods. The median ICD9 code saw a drop of 31% in utilization during the lockdown period, relative to the same period in 2019. We classify all ICD9 codes with a greater drop as more deferrable, and those with a smaller drop as less deferrable. Finally, we classify each visit as more or less deferrable based on the least deferrable code on that visit. Namely, if a visit has two diagnosis codes, one more deferrable and one less deferrable, we classify it as less deferrable.

# Appendix D Analysis Using an Alternative Post-Lockdown Period

To check the robustness of our results to the timing of the post period—right after the first COVID-19 lockdown in Israel—we reproduce key results using the exact same empirical specification but with a later post-lockdown period. As an alternative post-lockdown period we use the most recent data currently available from 2021, focusing on the period after a massive vaccination campaign in Israel has lead to full suppression of COVID-19 and complete reopening of the economy. We find that most results remain very similar. This section describes this exercise in detail.

## Sample and Variable Definitions

To construct the alternative sample we used the same inclusion and exclusion definitions as our main sample, but with the much later post-lockdown period spanning the period between April 5, 2021 and May 30, 2021. In the interim period between our original and alternative post-lockdown periods, Israel experienced two substantial waves of COVID-19 that were much more severe than the first wave, followed by a massive and successful vaccination campaign that essentially ended the COVID-19 epidemic in Israel. At the start of our alternative post-lockdown period, more than 90% of the adult population was fully vaccinated, and the sharp reduction COVID-19 cases that ensued from the vaccination campaign were nearly fully realized. Consequently, Israel has relaxed all restrictions except for indoor masking (which was also eliminated shortly after, in June 2021). The unemployment rate, which peaked at 21% in the thick of the pandemic, dropped to below 8%.

Appendix Figure A10 shows descriptive statistics on telemedicine use, COVID-19 cases, and primary care volume during the original study periods and leading up to our alternative post-lockdown period. Two facts emerge that motivate the focus on the alternative post-lockdown period. First, while there is a clear correlation between COVID-19 cases and telemedicine use throughout 2020–2021, telemedicine use also exhibits a ratchet effect: it remains at a much higher level than the pre-period baseline during both periods we observe during which Israel had nearly zero COVID-19 cases, including after the apparent end of the epidemic. In both our original and alternative post-lockdown periods, about 20% of new primary care episodes start remotely. Second, unlike the first post-lockdown period, which was preceded by a very sharp decrease in utilization of primary care (and healthcare services more generally) that was associated with the first COVID-19 lockdown, the rest of 2020 and the first half of 2021, saw a normalization of the pandemic and much higher rates of primary care utilization. Therefore, we argue that our alternative post period provides a useful context to study post-COVID-19 telemedicine use, and is less susceptible to concerns regarding the impact of COVID-19 and the disruption to healthcare utilization brought by it.

Using the alternative post-lockdown period, we consider the impact of increased access to telemedicine on the following outcomes: overall demand for primary care (defined as the probability of a non-followup primary care visit during the post period), in-visit actions during the index primary care visit, and physician follow-ups in the 7-day period following an index primary care visit. Because hospital claims become available for research with a six months lag, our spending measure for May 2021 are still incomplete, and thus we cannot calculate episode and overall spending.

We use the same empirical specification as in our main analysis. In particular, we use the same classification of physician propensity to use telemedicine, based on the (first) lockdown period. Patients affiliated with high adopters were much more likely to have remote visits in the alternative post-lockdown period: 30% of their primary care visits were conducted remotely, compared to only 12% for patients of low adopters. We also use the same pre period, with the appropriate adjustments. For the study of the impact of access to telemedicine on visit outcomes and 7-day physician followups, we use the exact same pre period as in our main analysis. For the study of the impact of access to telemedicine on primary care utilization, we compare primary care episodes that started during an alternative post-lockdown period against episodes that started during the same date range in 2019.

## Results

Table 5 and Appendix Figure A11 show estimates for the impact on different outcomes of increased access to telemedicine in the alternative post-lockdown period. Greater access to telemedicine is associated with a 3.5% increase in the share of members who have a primary care episode during the alternative post-lockdown period—nearly identical to the 3.5% increase estimated using the original post period. Similar to the original post period, increase access to telemedicine is associated with 4.4% lower rate of prescriptions during the index visit, and not associated with any significant increase in referrals. The estimated impacts on 7-day physician visits (+2.4%), visits with the same physician (+2.6%), and in-person visits (−4.9%) maintain the same sign as in our main analysis, though the magnitude of theses effects is smaller. Overall, the stability of our results over different periods suggests that they are not driven by idiosyncratic shocks specific to either period.

Appendix Figure A1: Remote Medicine Relative Use, by Diagnostic Category

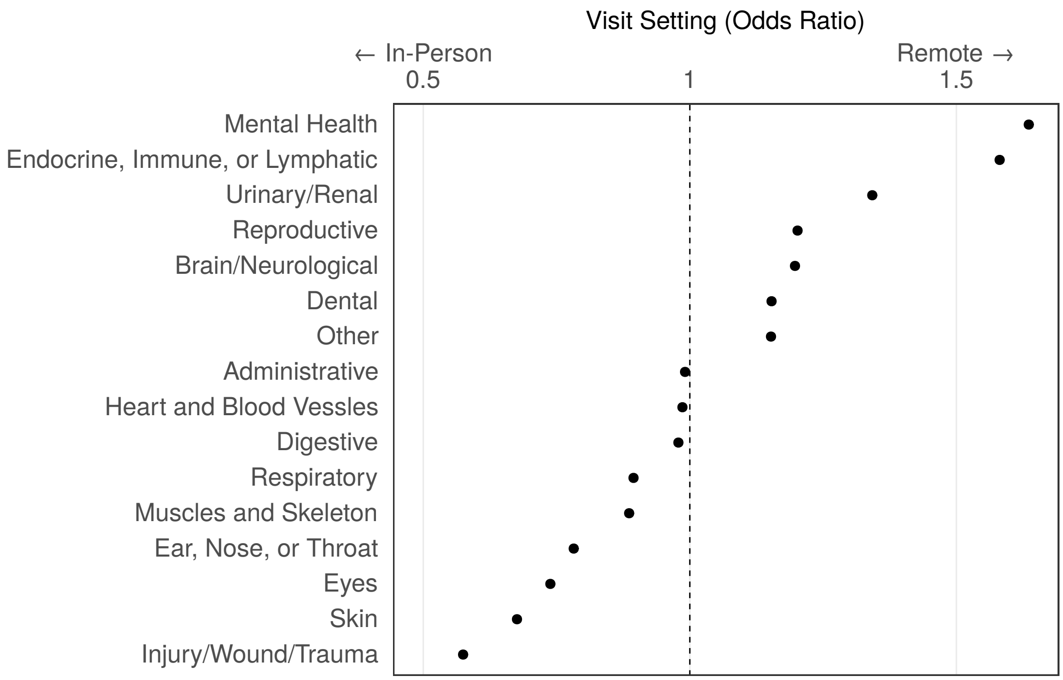



Figure shows the relative propensity of patients to use telemedicine (remote) versus in-person care for different categories of medical conditions. That is, using the post-lockdown sample of index (non-follow-up) primary care visits, the figure shows for each diagnostic category, the odds ratio (OR) of remote to in-person visits (i.e., $\frac{x/(1-x)}{y/(1-y)}$, where $x$ is the share of all remote visits that fall within the category and $y$ is the share of all in-person visits that fall within the category). An OR of one (marked by the dashed line) means that a category accounts for the same share of remote and in-person visits; categories with an OR greater than one are overrepresented in remote visits; categories with an OR smaller than one are underrepresented in remote visits. The sample construction is described in Section 2.2. The classification of visits is described in Appendix A.

Appendix Figure A2: Flexibly Estimated Time Trends in Additional Visit Outcomes, by Physician Telemedicine Use During the Lockdown Period

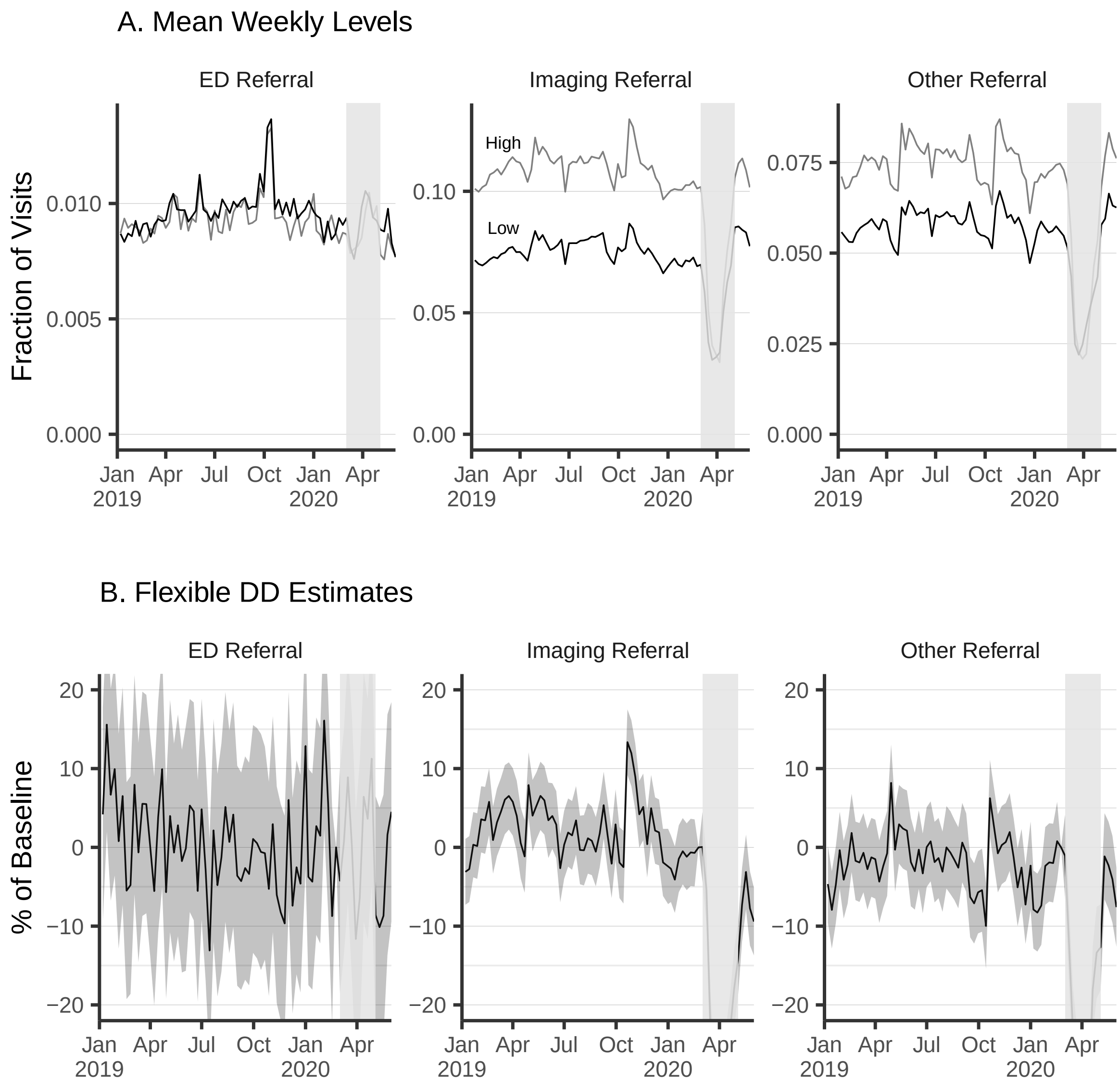



Figure shows, using the sample of all visits starting new primary care episodes, flexibly estimated time trends for all visit outcomes that were not included in Figure 4. Panel A shows raw (unadjusted) weekly means for visits of patients affiliated with high telemedicine adopters (High) and low telemedicine adopters (Low). Panel B shows flexible difference-in-differences estimates of the impact of high access to telemedicine from a version of equation (2) with the same fixed effects and controls but with fully flexible week dummies (and the same week dummies interacted with a dummy for High). The figure shows the estimates of week dummies interacted with dummy for High relative to the (omitted) last week of the pre-lockdown period. The 95% confidence interval is shown in dark gray. For comparability, estimates and their confidence intervals are expressed as a share (percent) of each mean outcome in the pre-lockdown period. The shaded light gray rectangles mark the lockdown period, which we only use for the measurement of telemedicine adoption but otherwise exclude from the analyses. Outcomes are not mutually exclusive. See Section 2.2 for detailed variable definitions.

Appendix Figure A3: Flexibly Estimated Time Trends in Physician Follow-Ups, by Physician Telemedicine Use During the Lockdown Period

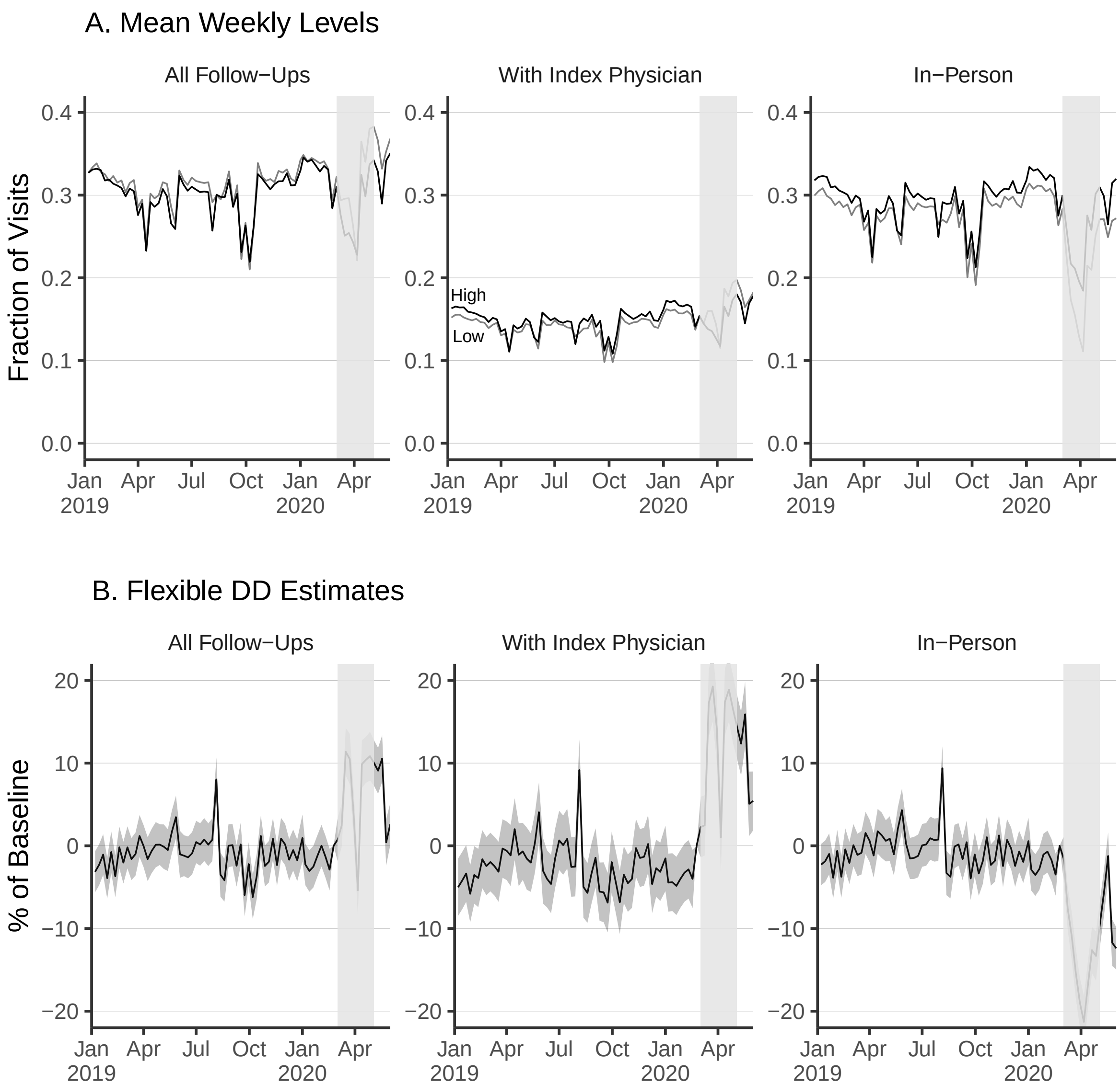



Figure shows, using the sample of all visits starting new primary care episodes, flexibly estimated time trends for 7-day physician follow-up visits. Panel A shows raw (unadjusted) weekly means for visits of patients affiliated with high telemedicine adopters (High) and low telemedicine adopters (Low). Panel B shows flexible difference-in-differences estimates of the impact of high access to telemedicine from a version of equation (2) with the same fixed effects and controls but with fully flexible week dummies (and the same week dummies interacted with a dummy for High). The figure shows the estimates of week dummies interacted with dummy for High relative to the (omitted) last week of the pre-lockdown period. The 95% confidence interval is shown in dark gray. For comparability, estimates and their confidence intervals are expressed as a share (percent) of each mean outcome in the pre-lockdown period. The shaded light gray rectangles mark the lockdown period, which we only use for the measurement of telemedicine adoption but otherwise exclude from the analyses. Outcomes are not mutually exclusive. See Section 2.2 for detailed variable definitions.

Appendix Figure A4: Placebo Analyses

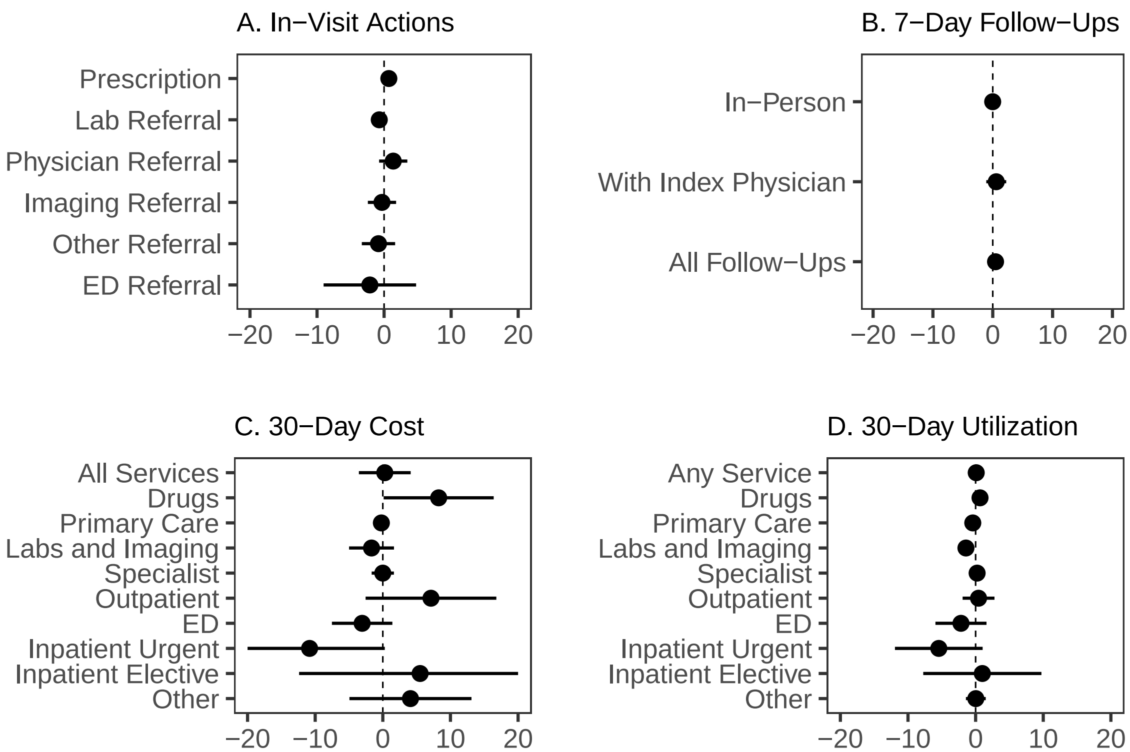



Figure shows placebo analyses. For each set of outcomes, we reproduce our main difference-in-differences estimates using equation (2), replacing the actual study sample with a “placebo” sample in which the pre period is January–February 2019 and the post period is January–February 2020. Because this placebo post period ended before widespread adoption of telemedicine began, we expect null results. Indeed, for nearly all outcomes, we cannot reject the null of no effect of (future) access to telemedicine on outcomes. Deviations are few and small in magnitude, possibly due to random variation of the outcomes. For ease of comparison, all coefficients are represented as a percent of the pre-period mean of each outcome.

Appendix Figure A5: Robustness: The Impact of Increased Access to Telemedicine on Index Visit Outcomes Using Alternative Access Measure

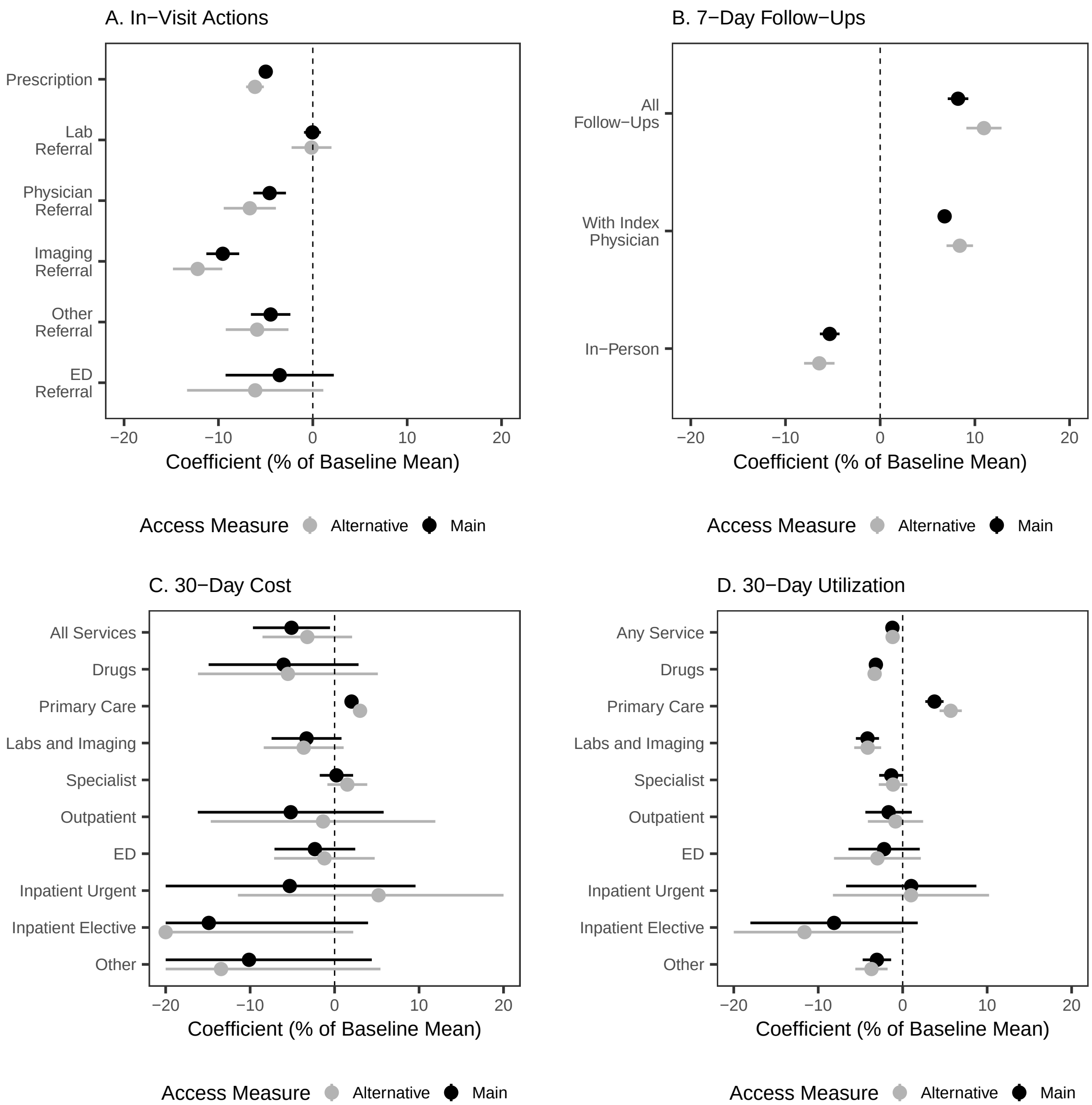



Figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, using an alternative measure of telemedicine access that is based on defining high and low access based on the top and bottom terciles of adopters; for ease of comparison, our main specification that is based on a definition of access that is based on above- and below-median adopters is also shown (see legend). The sample includes all new primary care episodes. Each row shows estimate of $\beta$ from equation (2) for a different outcome. This coefficient captures the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period. Panels A and B show outcomes of the first visit of each episode. Panels C and D show outcomes for services utilized during the 30-day period following the index visit. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 5.1 discusses in more detail the sample and variable definitions.

Appendix Figure A6: The Impact of Increased Access to Telemedicine on Visit Outcomes, Follow-Ups, and 30-Day Cost and Utilization, by Deferrability of Diagnoses

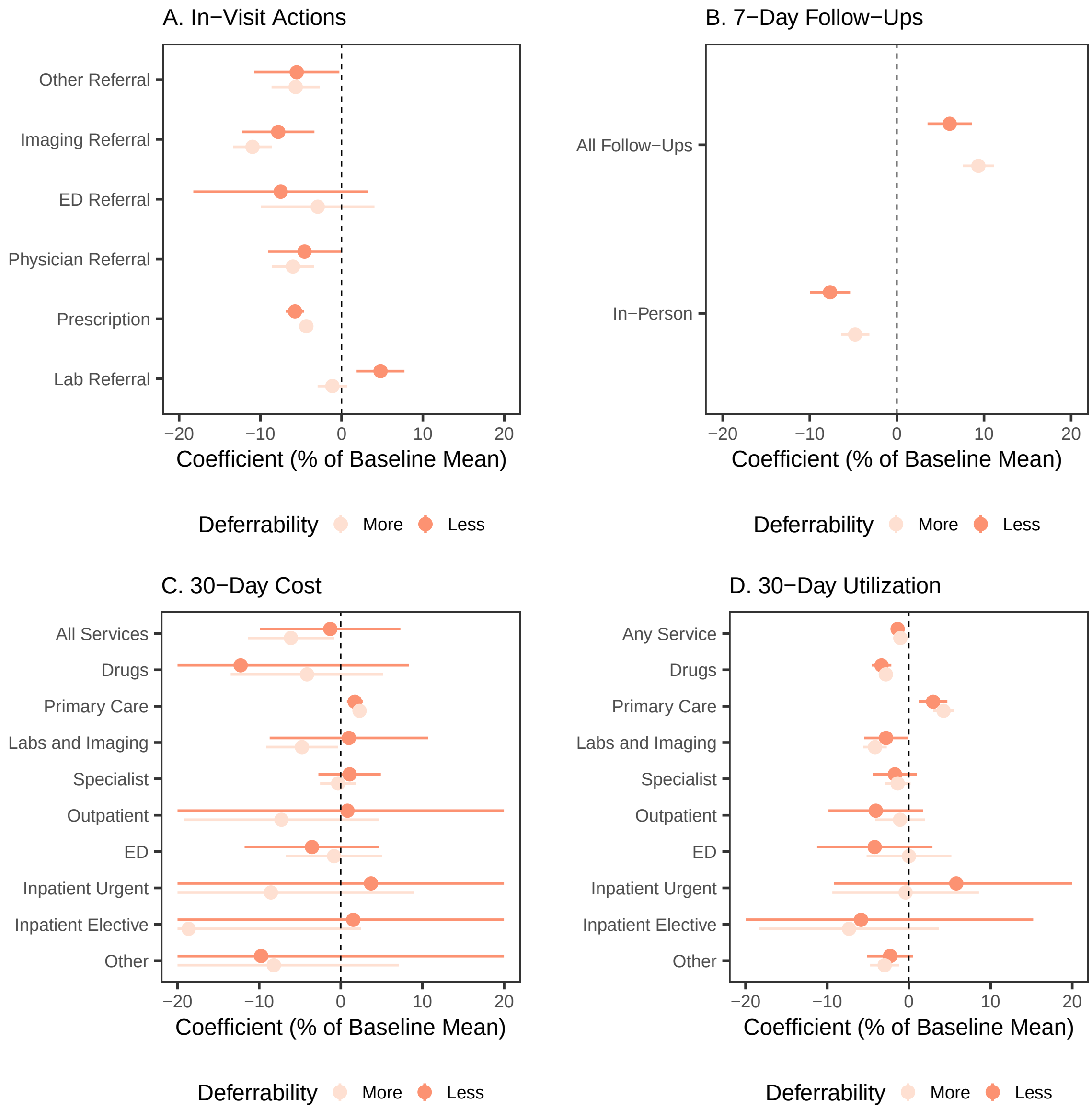



Figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by the deferrability of the medical diagnosis associated with the index visit (see legend). The sample includes all new primary care episodes. Each row shows estimate of $\beta$ from equation (2) for a different outcome. This coefficient captures the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period. Panels A and B show outcomes of the first visit of each episode. Panels C and D show outcomes for services utilized during the 30-day period following the index visit. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 5.1 discusses in more detail the sample and variable definitions.

Appendix Figure A7: The Impact of Increased Access to Telemedicine on Visit Outcomes, Follow-Ups, and 30-Day Cost and Utilization, by Patient Age

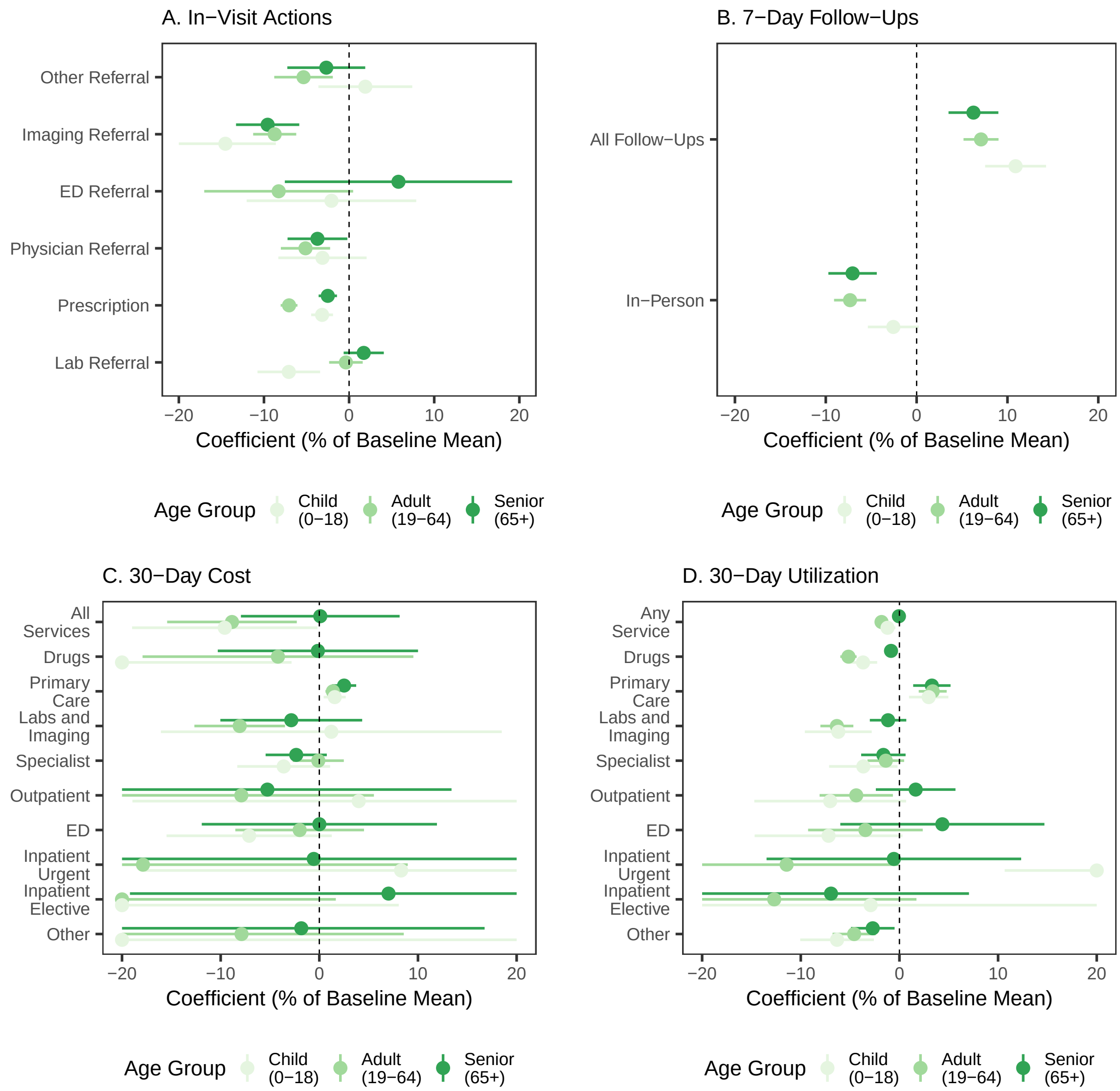



Figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different ages at the time of the first visit (see legend). The sample includes all new primary care episodes. Each row shows estimate of $\beta$ from equation (2) for a different outcome. This coefficient captures the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period. Panels A and B show outcomes of the first visit of each episode. Panels C and D show outcomes for services utilized during the 30-day period following the index visit. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 5.2 discusses in more detail the sample and variable definitions.

Appendix Figure A8: The Impact of Increased Access to Telemedicine on Visit Outcomes, Follow-Ups, and 30-Day Cost and Utilization, by Patient Gender

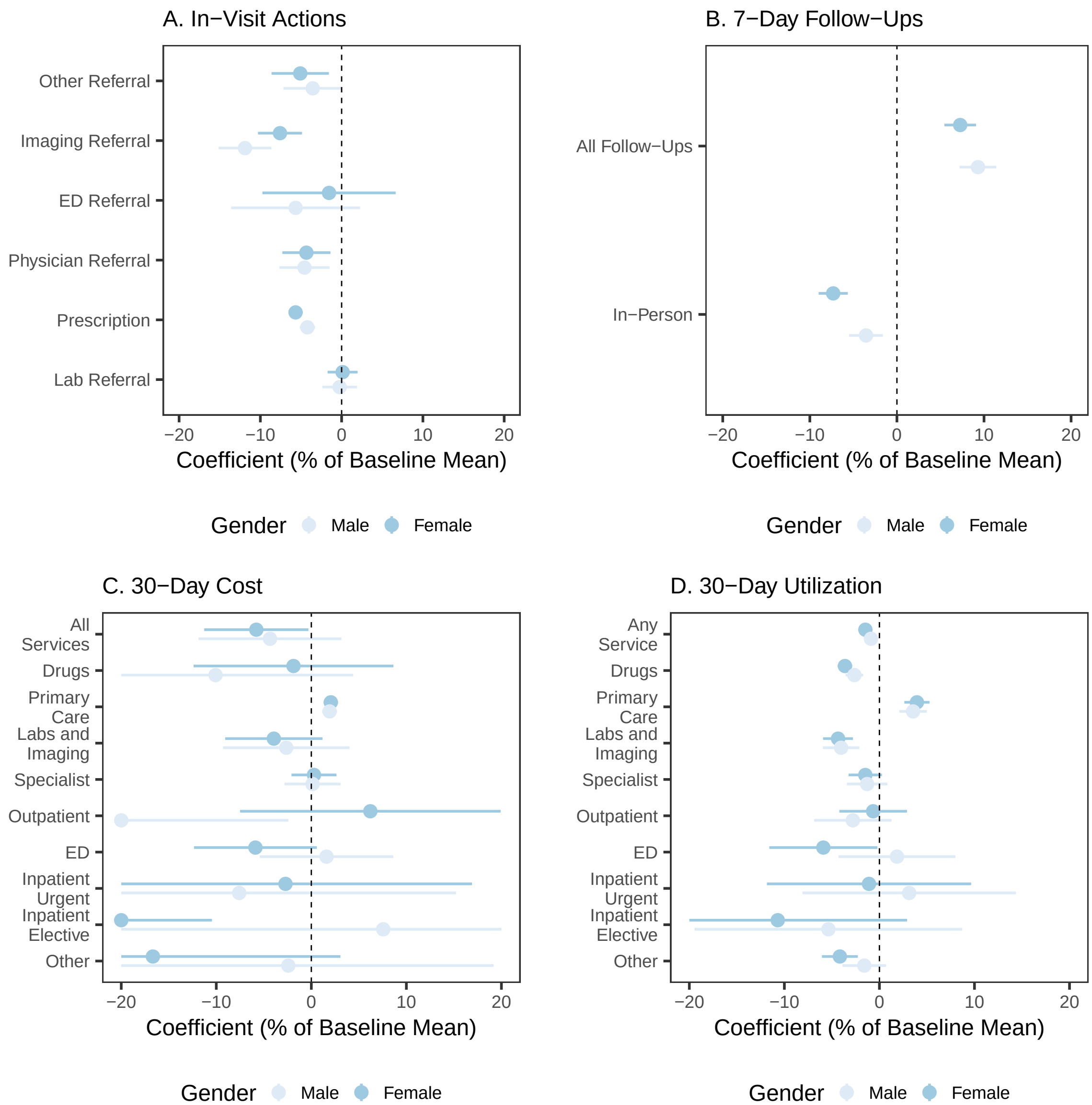



Figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different genders (see legend). The sample includes all new primary care episodes. Each row shows estimate of $\beta$ from equation (2) for a different outcome. This coefficient captures the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period. Panels A and B show outcomes of the first visit of each episode. Panels C and D show outcomes for services utilized during the 30-day period following the index visit. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 5.2 discusses in more detail the sample and variable definitions.

Appendix Figure A9: The Impact of Increased Access to Telemedicine on Visit Outcomes, Follow-Ups, and 30-Day Cost and Utilization, by Socioeconomic Status

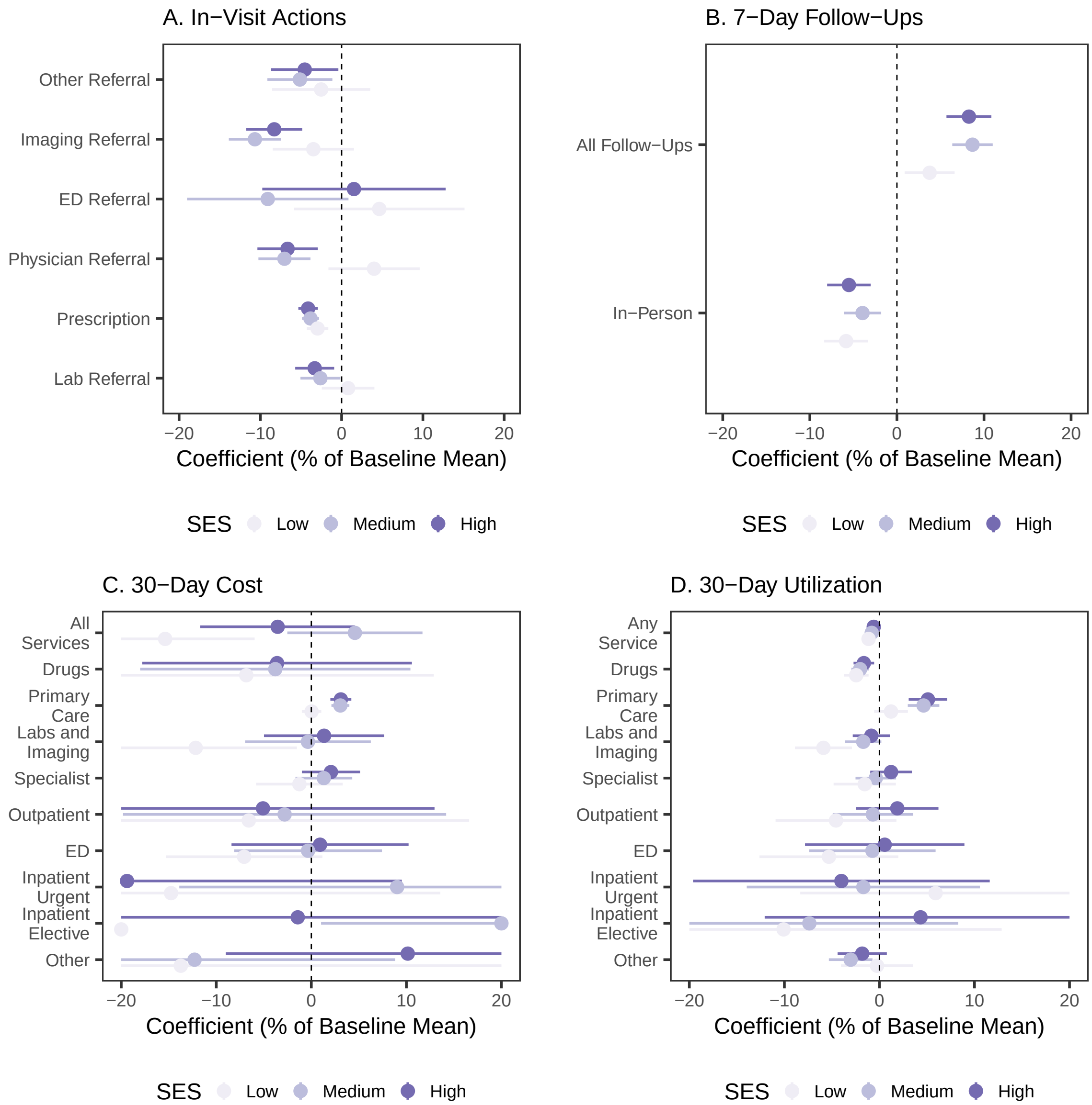



Figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different terciles of a socioeconomic status score defined based on the average income at the patient place of residence (see legend). The sample includes all new primary care episodes. Each row shows estimate of $\beta$ from equation (2) for a different outcome. This coefficient captures the difference in differences in the change between the pre- and post-lockdown periods between patients with high and low access to telemedicine. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period. Panels A and B show outcomes of the first visit of each episode. Panels C and D show outcomes for services utilized during the 30-day period following the index visit. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Estimates and confidence intervals with values above 20% or below −20% are winsorized. Section 5.2 discusses in more detail the sample and variable definitions.

Appendix Figure A10: Share of Visits Provided Remotely, COVID-19 Cases, and Average Primary Care Utilization 2020–2021

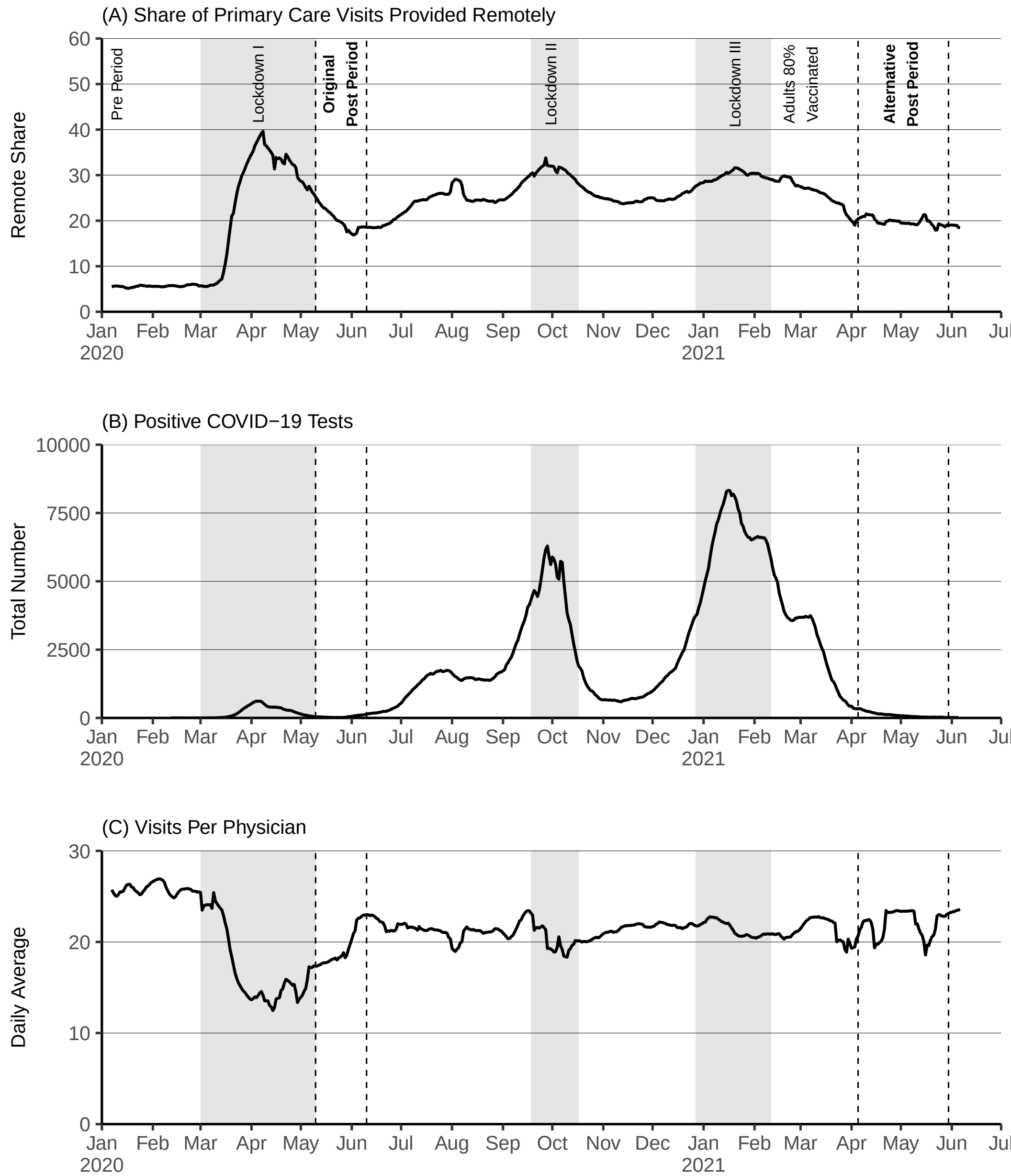



Figure shows different statistics for the period leading up to our alternative post-lockdown period. Gray-shaded areas refer to lockdown periods and the areas between the two vertical dashed lines refer to this study's original and alternative post-lockdown periods (original: May 11, 2020 to June 7, 2020; alternative: April 5, 2021 to May 30, 2021). For details, see Section 2.2 and Appendix D. Panel A shows the daily percent of primary care visits provided remotely. Panel B shows the daily number of new confirmed COVID-19 cases. Panel C shows the daily number of visits (both remote and in person) performed by primary care physicians in our study sample. All data series were smoothed using 7-day moving average. Partial series start when data are first available. Data source: Clalit Health Services (Panels A and C) and Israel's Ministry of Health (Panel B and information about lockdown periods and vaccination rates).

Appendix Figure A11: The Impact of Increased Access to Telemedicine on Index Visit In-Visit Actions and 7-Day Follow-Ups, Alternative Post-Lockdown Period

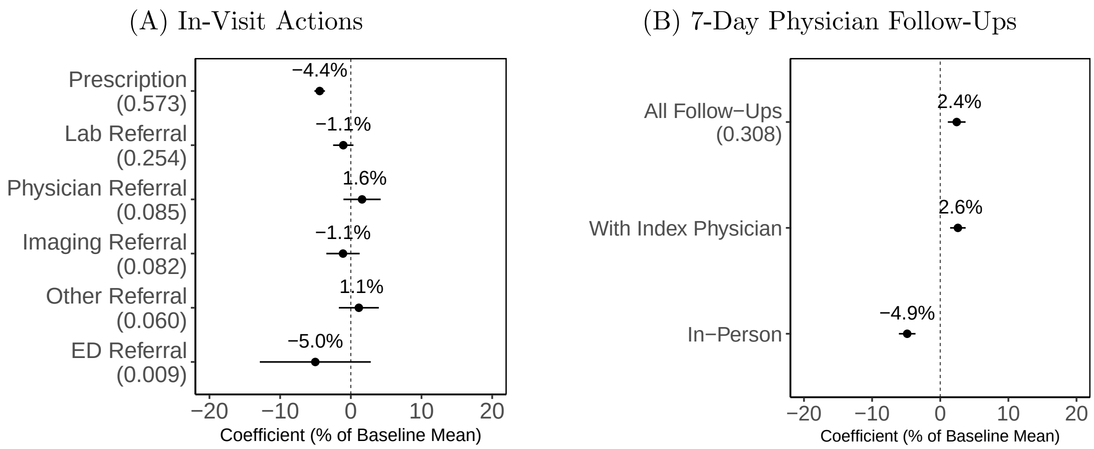



Figure shows the estimated impacts of increased access to telemedicine on visit outcomes using the alternative post-lockdown period of April–May 2021. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine ($\beta$ from equation (2)) for a different outcome. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period (shown in parenthesis). In Panel B, all coefficients are represented as a percent of the mean of all follow-ups (0.308). The sample includes all new primary care episodes that took place in the pre-lockdown period of January 2019–February 2020 and the alternative post-lockdown period of April–May 2021. Outcomes shown are for the first visit of each episode. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Appendix D discusses the sample details.

Appendix Table A1: Target Conditions and Differential Diagnoses for the UTI Sample

| ICD9 Code (1) | Diagnosis (2) | Number of Visits (3) |
|---|---|---|
| **A. Target Conditions** | | |
| 599.0 | Urinary Tract Infection | 5,532 |
| 595.0 | Cystitis Acute | 173 |
| 595 | Cystitis | 164 |
| 590.1 | Pyelonephritis Acute | 57 |
| **B. Differential Diagnoses** | | |
| 788.1 | Dysuria | 3,941 |
| 788.3 | Urinary Incontinence | 1,728 |
| 788.4 | Urinary Frequency | 1,068 |
| 600.0 | Prostatic Enlargement | 1,016 |
| 788.0 | Renal Colic | 714 |
| 616.1 | Vaginitis | 574 |
| 600.9 | Prostatic Hyperplasia | 415 |
| 788.2 | Urine Retention | 155 |
| 597 | Urethritis | 68 |
| 614 | Pelvic Inflammatory Disease | 39 |
| 597.8 | Meatitis | 17 |
| 616.3 | Bartholins Abscess | 15 |
| All | | 15,727 |

The table shows the distribution of diagnoses in visits that are included in our sample of UTI and related conditions. Panel A shows data for diagnoses that we define as the target condition (UTI). Panel B shows data for diagnoses that we define as related differential diagnoses. See Appendix B for details of the sample construction and variable definitions. The sum of visits is greater than the sample size because some visits record multiple diagnoses.

Appendix Table A2: Target Conditions and Differential Diagnoses for the AMI Sample

| ICD9 Code<br>(1) | Diagnosis<br>(2) | Number of Visits<br>(3) |
|---|---|---|
| **A. Target Conditions** | | |
| 410 | Myocardial Infarction | 226 |
| 410.4 | Myocardial Infarction Inferior NOS | 14 |
| 410.0 | Myocardial Infarction Anterolateral | 11 |
| **B. Differential Diagnoses** | | |
| 786.5 | Chest Pain | 5,439 |
| 530.1 | Reflux Esophageal | 2,508 |
| 486 | Pneumonia | 2,448 |
| 053.9 | Herpes Zoster | 773 |
| 413.9 | Dyspnea Effort | 689 |
| 485 | Bronchopneumonia | 458 |
| 511.8 | Pleural Effusion NOS | 73 |
| 162.3 | Malignant Neoplasm Lung | 72 |
| 415.1 | Pulmonary Embolism | 51 |
| 483 | Pneumonia Mycoplasma | 47 |
| 533 | Peptic Ulcer Site Unspecified | 44 |
| 420 | Pericarditis | 38 |
| 860 | Pneumothorax Traumatic | 32 |
| 053.1 | Post Herpetic Neuralgia | 28 |
| 530.0 | Achalasia | 26 |
| 480 | Pneumonia Viral | 21 |
| 483.1 | Chlamydia | 19 |
| 422.9 | Myocarditis Acute Unspecified | 18 |
| 511.9 | Pleural Effusion Unspecified | 18 |
| 511 | Pleurisy | 13 |
| 875 | Laceration Chest | 10 |
| All | | 13,119 |

The table shows the distribution of diagnoses in visits that are included in our sample of AMI and related conditions. Panel A shows data for diagnoses that we define as the target condition (AMI). Panel B shows data for diagnoses that we define as related differential diagnoses. See Appendix B for details of the sample construction and variable definitions. The sum of visits is greater than the sample size because some visits record multiple diagnoses.

Appendix Table A3: Target Conditions and Differential Diagnoses for the Trauma Sample

| ICD9 Code (1) | Diagnosis (2) | Number of Visits (3) |
|---|---|---|
| **A. Target Conditions** | | |
| 813.0 | Fracture Radius | 251 |
| 816.0 | Fracture Finger | 237 |
| 805 | Fracture Vertebral Column | 183 |
| 813.4 | Fracture Radius Distal | 133 |
| 824 | Fracture Ankle | 131 |
| 825.2 | Fracture Metatarsal(s) Closed | 115 |
| 807.0 | Fracture Ribs Closed | 95 |
| 823.0 | Fracture Tibia | 83 |
| 812 | Fracture Humerus | 81 |
| 820 | Fracture Hip | 74 |
| 807 | Fracture Rib | 72 |
| 825 | Fracture Metatarsal | 64 |
| 820.2 | Fracture Femur Intertrochanteric Closed | 63 |
| 814.0 | Fracture Scaphoid Closed | 58 |
| 802.0 | Fracture Nose | 56 |
| 812.0 | Fracture Humerus Greater Tuberosity Closed | 54 |
| **B. Differential Diagnoses** | | |
| 845.0 | Ankle Sprain | 1,058 |
| 847.0 | Whiplash Injury | 690 |
| 879.8 | Wound Open | 620 |
| 859.0 | Head Trauma | 593 |
| 873.4 | Laceration Face | 342 |
| 883 | Laceration Fingers | 335 |
| 892 | Laceration Foot | 279 |
| 882 | Laceration Hand | 266 |
| 836.0 | Meniscus Tear Medial Current | 138 |
| 831 | Shoulder Dislocation | 103 |
| 891 | Laceration Knee Leg And Ankle | 103 |
| 873.6 | Laceration Mouth | 64 |
| 844.0 | Sprain Knee | 62 |
| 845.1 | Sprain Foot | 61 |
| 848.1 | Temporomandibular Joint Strain | 60 |
| 847.2 | Strain Lumbar | 55 |
| All | | 9,415 |

We suppressed cells with fewer than 50 observations from this table (we did include them in the analysis). The table shows the distribution of diagnoses in visits that are included in our sample of bone fractures and related conditions. Panel A shows data for diagnoses that we define as the target condition (bone fractures). Panel B shows data for diagnoses that we define as related differential diagnoses. See Appendix B for details of the sample construction and variable definitions. The sum of visits is greater than the sample size because some visits record multiple diagnoses.

Appendix Table A4: Patient Characteristics, Specific Conditions

| | UTI (1) | AMI (2) | Fracture (3) |
|---|---|---|---|
| **A. All Conditions** | | | |
| Age | 43.6 | 53.3 | 35.2 |
| Female | 0.669 | 0.506 | 0.414 |
| ACG | 1.46 | 1.84 | |
| Number of Chronic Conditions | 0.155 | 0.201 | 0.122 |
| **B. UTI** | | | |
| UTI in Last Year | 0.204 | | |
| Number of UTI Months in Last 5 Years | 2.08 | | |
| **C. AMI** | | | |
| Smoker | | 0.183 | |
| Systolic BP | | 123.6 | |
| Total Cholesterol | | 176.6 | |
| HDL Cholesterol | | 48.4 | |
| History of Anti Hypertensives | | 0.433 | |
| History of Diabetes | | 0.293 | |
| **D. Fracture** | | | |
| History of Osteoporosis | | | 0.066 |
| Head Injury | | | 0.077 |
| Torso Injury | | | 0.148 |
| Arm Injury | | | 0.234 |
| Leg Injury | | | 0.183 |
| Number of Physicians | 3,309 | 2,570 | 2,801 |
| Number of Visits | 14,877 | 10,105 | 8,550 |

Table shows summary statistics for all control variables that we use in the analysis of specific conditions. The different columns show data for the three samples: UTI, AMI, and bone fractures. These samples include each target condition and related differential diagnoses. Panel A shows risk-factors that are common to all conditions and used as controls in all regressions. Panels B–D show risk factors (used as controls) that are specific to each condition. Sample construction and variable definitions are discussed in Appendix B.

Appendix Table A5: The Impact of Increased Access to Telemedicine on Utilization, by Age, Gender, and Socioeconomic Status

| | Any Healthcare Utilization | | | Any Primary Care Episode | | | Total Healthcare Cost (NIS) | | | Total Cost of Primary Care Episodes (NIS) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est. (1) | (S.E.) (2) | % (3) | Est. (4) | (S.E.) (5) | % (6) | Est. (7) | (S.E.) (8) | % (9) | Est. (10) | (S.E.) (11) | % (12) |
| **A. Specification** | | | | | | | | | | | | |
| Main Specification | 0.0014 | (0.0007) | 0.3% | 0.0063 | (0.0005) | 3.5% | -14 | (7) | -3.0% | -6 | (2) | -5.7% |
| Alternative Access Measure | 0.0024 | (0.0008) | 0.5% | 0.0098 | (0.0006) | 5.5% | -21 | (9) | -4.4% | -6 | (3) | -5.6% |
| **B. Age Group** | | | | | | | | | | | | |
| Child (0–18) | -0.0031 | (0.0012) | -0.8% | 0.0023 | (0.0009) | 1.2% | -10 | (8) | -6.3% | -2 | (3) | -3.4% |
| Adult (19–64) | -0.0056 | (0.0009) | -1.1% | 0.0002 | (0.0007) | 0.1% | -13 | (8) | -3.1% | -9 | (3) | -9.3% |
| Senior (65+) | -0.0113 | (0.0014) | -1.3% | -0.0073 | (0.0014) | -3.8% | 1 | (29) | 0.1% | -15 | (9) | -6.1% |
| **C. Gender** | | | | | | | | | | | | |
| Male | 0.0021 | (0.0009) | 0.4% | 0.0058 | (0.0007) | 3.4% | -14 | (10) | -2.9% | -8 | (4) | -7.5% |
| Female | 0.0007 | (0.0009) | 0.1% | 0.0066 | (0.0007) | 3.6% | -13 | (8) | -2.8% | -4 | (3) | -3.7% |
| **D. SES** | | | | | | | | | | | | |
| Low | -0.0064 | (0.0012) | -1.5% | -0.0026 | (0.0010) | -1.5% | -14 | (10) | -3.9% | -14 | (5) | -14.4% |
| Medium | 0.0091 | (0.0011) | 1.6% | 0.0140 | (0.0009) | 7.7% | -6 | (12) | -1.1% | 8 | (4) | 6.8% |
| High | 0.0105 | (0.0012) | 1.8% | 0.0126 | (0.0010) | 7.2% | -8 | (13) | -1.5% | -1 | (4) | -0.9% |

The table shows alternative estimates for the impacts of increased access to telemedicine on utilization and total cost of care for specific subsamples. Cells show estimates of $\beta$ from equation (2) for different outcomes, the standard errors (in parentheses), and the estimates scaled as a percent of pre-lockdown mean for each outcome. We have four outcomes: any healthcare utilization is any service use; any primary care episode refer to care episodes starting with a primary care visit that had no other encounters in the 14 days preceding it. Total healthcare cost is the sum of costs of all services during period. Total cost of new primary care episodes includes all services utilized within 30 days of the index visit data. The sample includes all members, including those with zero utilization. Each row shows results for a different specification or subsample. Baseline repeats our main specification. Robustness reproduces the results with an alternative definition of access to telemedicine, discussed in Section 5.1. Panels A–C show results for subsamples defined by gender, age, and SES groups. These are discussed in Section 5.2.

Appendix Table A6: The Impact of Increased Access to Telemedicine on Total Cost of Care and Utilization, by Deferrability of Diagnoses in Index Visit

| | Pre-Lockdown Mean | Estimated Impact | (S.E.) | Percentage Impact |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A. Any Primary Care Episode** | | | | |
| More Deferrable | 0.111 | -0.0003 | (0.0004) | -0.3% |
| Less Deferrable | 0.068 | 0.0066 | (0.0003) | 9.8% |
| **B. Total Cost of Primary Care Episodes (NIS)** | | | | |
| More Deferrable | 72 | -7 | (2) | -9.7% |
| Less Deferrable | 32 | 1 | (1) | 3.1% |

The table shows the estimated impacts of increased access to telemedicine on utilization and total cost of care by deferrability of the index condition. Each panel shows estimates of the impact of access to telemedicine ($\beta$ from the model specified in equation (2)) for a different outcome: any primary care episode is an indicator variable for whether the member had any care episodes starting with an index primary care visit that had no other encounters in the 14 days preceding it. Total cost of new primary care episodes is the sum of all services utilized within 30 days of such index visit. Each row shows an estimate for a different subset of visits, based on how deferrable the index visit diagnosis is. We consider diagnoses with an above-median drop during lockdown as more deferrable and the rest as less deferrable. Appendix C discusses the details of the deferrability definition and sample construction.

Appendix Table A7: Patient Characteristics, Different Subsamples

| | Age Group | | | Gender | | SES | | |
|---|---|---|---|---|---|---|---|---|
| | Child | Adult | Senior | Female | Male | Low | Medium | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **A. Patient Characteristics** | | | | | | | | |
| Female | 0.482 | 0.576 | 0.578 | 0.290 | 0.291 | 0.546 | 0.551 | 0.548 |
| Age | 7.4 | 41.2 | 74.7 | 39.0 | 35.4 | 33.9 | 38.6 | 40.0 |
| ACG | 0.538 | 0.978 | 2.084 | 1.082 | 1.022 | 0.982 | 1.112 | 1.075 |
| Number of Chronic Conditions | 0.432 | 2.347 | 6.899 | 2.639 | 2.629 | 2.259 | 2.867 | 2.801 |
| **B. In-Visit Actions** | | | | | | | | |
| Prescription | 0.458 | 0.502 | 0.581 | 0.517 | 0.488 | 0.547 | 0.496 | 0.461 |
| Lab Referral | 0.241 | 0.325 | 0.386 | 0.327 | 0.292 | 0.264 | 0.329 | 0.346 |
| Physician Referral | 0.067 | 0.101 | 0.121 | 0.090 | 0.100 | 0.074 | 0.105 | 0.105 |
| Imaging Referral | 0.037 | 0.097 | 0.140 | 0.089 | 0.085 | 0.068 | 0.095 | 0.099 |
| Other Referral | 0.060 | 0.063 | 0.076 | 0.062 | 0.067 | 0.047 | 0.070 | 0.080 |
| ED Referral | 0.009 | 0.007 | 0.007 | 0.007 | 0.008 | 0.009 | 0.007 | 0.006 |
| **C. Number of 7-Day Physician Follow-Ups** | | | | | | | | |
| All Follow-Ups | 0.309 | 0.347 | 0.375 | 0.353 | 0.327 | 0.321 | 0.350 | 0.354 |
| With Index Physician | 0.146 | 0.176 | 0.206 | 0.179 | 0.164 | 0.162 | 0.178 | 0.179 |
| Not With Index Physician | 0.163 | 0.171 | 0.169 | 0.174 | 0.162 | 0.159 | 0.172 | 0.176 |
| Remote | 0.059 | 0.057 | 0.059 | 0.063 | 0.052 | 0.031 | 0.065 | 0.080 |
| In-Person | 0.251 | 0.290 | 0.316 | 0.290 | 0.275 | 0.289 | 0.284 | 0.274 |
| **D. 30-Day Cost Outcomes (NIS)** | | | | | | | | |
| All Services | 319 | 643 | 1260 | 643 | 685 | 637 | 676 | 676 |
| Drugs | 50 | 130 | 277 | 129 | 139 | 114 | 139 | 152 |
| Inpatient Urgent | 48 | 106 | 331 | 111 | 156 | 131 | 138 | 123 |
| Primary Care | 84 | 90 | 98 | 91 | 87 | 90 | 89 | 88 |
| Inpatient Elective | 27 | 93 | 181 | 82 | 99 | 108 | 83 | 76 |
| Labs and Imaging | 29 | 84 | 118 | 83 | 62 | 62 | 78 | 83 |
| Outpatient | 16 | 54 | 119 | 56 | 54 | 49 | 55 | 62 |
| Specialist | 20 | 37 | 58 | 38 | 33 | 30 | 38 | 40 |
| ED | 18 | 25 | 23 | 22 | 23 | 24 | 22 | 19 |
| Other | 27 | 24 | 56 | 31 | 31 | 29 | 34 | 31 |
| Number of Visits | 166,606 | 283,875 | 105,156 | 304,567 | 251,070 | 193,777 | 200,068 | 161,318 |
| Remote Share of Visits | 0.151 | 0.193 | 0.208 | 0.194 | 0.169 | 0.103 | 0.197 | 0.263 |

Table shows patient, visit, and episode characteristics for different subsamples used in the analysis of heterogeneity. The sample includes the post-lockdown period; its construction is discussed in Section 2.2. Costs are in current New Israeli Shekels (NIS).

Appendix Table A8: The Impact of Access to Telemedicine on Visit and Episode Outcomes

| | Pre-Lockdown Mean | Estimated Impact | (S.E.) | Percentage Impact |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A. In-Visit Actions** | | | | |
| Prescription | 0.573 | -0.0286 | (0.0013) | -5.0% |
| Lab Referral | 0.254 | -0.0001 | (0.0012) | 0.0% |
| Physician Referral | 0.085 | -0.0039 | (0.0007) | -4.6% |
| Imaging Referral | 0.082 | -0.0079 | (0.0007) | -9.5% |
| Other Referral | 0.060 | -0.0027 | (0.0006) | -4.5% |
| ED Referral | 0.009 | -0.0003 | (0.0003) | -3.5% |
| **B. Number of 7-Day Physician Follow-Ups** | | | | |
| All Follow-Ups | 0.308 | 0.0253 | (0.0017) | 8.2% |
| With Index Physician | 0.147 | 0.0210 | (0.0011) | 14.3% |
| Not With Index Physician | 0.160 | 0.0044 | (0.0012) | 2.7% |
| Remote | 0.018 | 0.0417 | (0.0004) | 228.0% |
| In-Person | 0.289 | -0.0164 | (0.0016) | -5.7% |
| **C. 30-Day Utilization** | | | | |
| All Services | 0.855 | -0.0104 | (0.0015) | -1.2% |
| Drugs | 0.673 | -0.0214 | (0.0023) | -3.2% |
| Primary Care | 0.422 | 0.0159 | (0.0023) | 3.8% |
| Labs and Imaging | 0.342 | -0.0143 | (0.0024) | -4.2% |
| Specialist | 0.248 | -0.0034 | (0.0018) | -1.4% |
| Outpatient | 0.080 | -0.0013 | (0.0011) | -1.7% |
| ED | 0.031 | -0.0007 | (0.0007) | -2.2% |
| Inpatient Urgent | 0.009 | 0.0001 | (0.0003) | 1.0% |
| Inpatient Elective | 0.006 | -0.0005 | (0.0003) | -8.1% |
| Other | 0.268 | -0.0082 | (0.0023) | -3.1% |
| **D. 30-Day Cost (NIS)** | | | | |
| All Services | 565 | -28.84 | (13.1588) | -5.1% |
| Drugs | 118 | -7.13 | (5.3432) | -6.0% |
| Primary Care | 86 | 1.73 | (0.2720) | 2.0% |
| Labs and Imaging | 58 | -1.93 | (1.2268) | -3.3% |
| Specialist | 30 | 0.06 | (0.2982) | 0.2% |
| Outpatient | 44 | -2.26 | (2.4474) | -5.2% |
| ED | 24 | -0.56 | (0.5830) | -2.3% |
| Inpatient Urgent | 112 | -5.95 | (8.5119) | -5.3% |
| Inpatient Elective | 70 | -10.38 | (6.7054) | -14.9% |
| Other | 24 | -2.42 | (1.7725) | -10.1% |

Table shows the estimated impacts of increased access to telemedicine on different outcomes. The sample includes all new primary care episodes. Each panel shows estimates of the impact of access to telemedicine ($\beta$ from the model specified in equation (2)) for a different set of outcomes. For ease of comparison, all coefficients are represented as a percent of the baseline mean—the mean of the outcome during the pre-lockdown period (shown in parentheses). Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive.