THE IMPACT OF INCREASED ACCESS TO TELEMEDICINE

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Abstract
We estimate the impact of increased access to telemedicine following widespread adoption during the March–April 2020 COVID-19 lockdown period. We focus on the post-lockdown period, which was characterized by near-complete reopening. 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, as defined by their primary care physician adoption. Our results show that access to telemedicine leads to slightly more primary care visits but lower spending. Visits involve fewer prescriptions and more follow-ups, but we find no evidence of missed diagnoses or adverse outcomes. Results suggest that telemedicine does not compromise care quality or raise costs. (JEL: I11, O33)

Teaching Slides
A set of Teaching Slides to accompany this article is available online as Supplementary Data.

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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 healthcare provision. Just like e-commerce has revolutionized retail, so the argument goes, telemedicine could 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, Edmunds, and Hodgkins 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 abruptly changed with the COVID-19 pandemic, which 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 most developed countries, the share of remote visits rose sharply once hurdles were swiftly lifted in the wake of COVID-19 and then stabilized at much higher levels than before the pandemic (Mehrotra et al. 2020a; Patel et al. 2020; Hatef et al. 2022).[2] The rapid growth of telemedicine and the broadening of clinicians' licenses to use it raise the question of what will become of these new approaches to treatment once COVID-19 reaches its endemic stage (Cutler, Nikpay, and Huckman 2020; Dorsey and Topol 2020).

Providing care remotely entails both risks and opportunities. On the positive side, telemedicine can improve access to care and make receiving care much more convenient (Hollander and Carr 2020). It may also expand the geographic reach of providers (Dahlstrand 2021; Goetz Forthcoming) and reduce the costs of follow-up encounters, thus 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 to guide the future, post-pandemic use of remote medicine. In this study, we attempt to start filling this gap by taking advantage of a unique situation created in Israel during and shortly after the first COVID-19 wave,

1. Examples of media coverage include the following: 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; and "A Digital Revolution in Health Care Is Speeding Up," *The Economist*, March 4, 2017.

2. By early 2021, 45% of the patients in OECD countries reported having used telemedicine at least once since the COVID-19 pandemic began (OECD 2021). In the United States, the figure was 88% (Cordine et al. 2022). Widespread adoption also spurred large investments in digital health innovations. For example, total funding among US-based digital health startups was $29.1 billion in 2021, up from $8.2 billion in 2019 (Rock Health 2021).

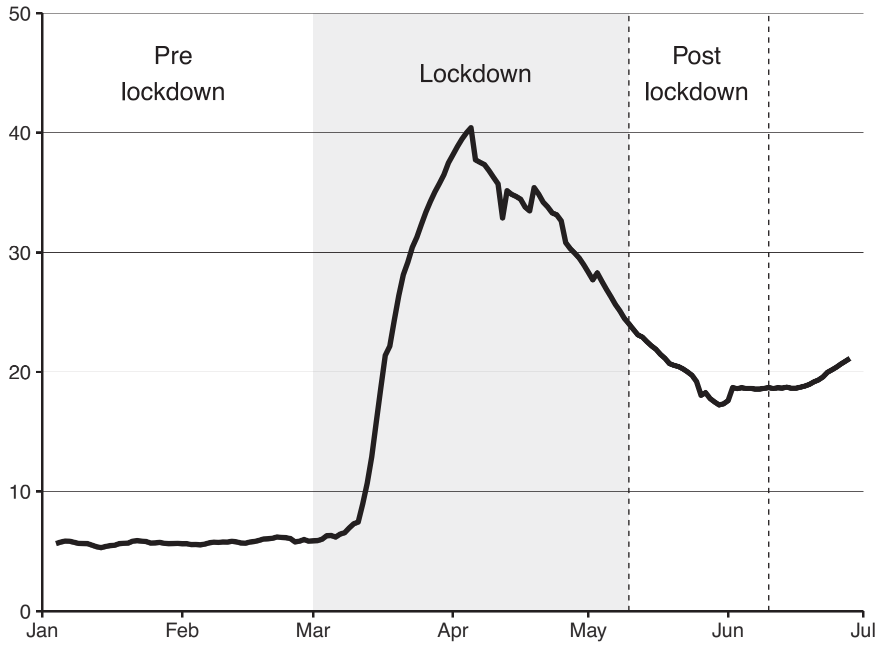


FIGURE 1. Share of primary care visits provided remotely in 2020. The figure shows a 7-day moving average of the daily percent of primary care visits provided remotely. Labels refer to the study periods. See Section 2.2 for detailed definitions.

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 were low.[3]

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

3. By the end of our study period, only about one in a thousand Israelis had tested positive for COVID-19 (despite widespread testing), and only 200 died of it, out of a population of 9 million.

entirety and use data from electronic medical records (EMRs) that are typically not observed in claims data, such as blood test results. 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.

We begin by documenting physician adoption of telemedicine, which we index by physicians' tendency to shift to remote care during the COVID-19 lockdown period (March–April 2020), adjusting for case mix, time, and place. We document several patterns. First, telemedicine adoption is heterogeneous. For example, younger and female physicians were more likely to adopt telemedicine during the first lockdown period. Second, adoption is persistent: Initially high adopters (and their patients) still used telemedicine at higher rates post-lockdown, even a year later, when most of the Israeli population was fully vaccinated and COVID-19 restrictions were nearly eliminated (before the Delta and Omicron COVID-19 variants appeared). Finally, within-physician adoption is fairly uniform across different patient types (younger and older, sicker and healthier, male and female). Therefore, telemedicine use by physicians can be compactly summarized using a one-dimensional index, which we refer to as the physician's *telemedicine adoption*.

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, whereas the latter do. To address this challenge, our empirical strategy does not rely on the actual visit setting. Instead, it focuses on patients' *access to telemedicine*, which we measure based on the decision of a patient's regular primary care physician to adopt telemedicine. We consider physicians whose telemedicine adoption was above the 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.[4]

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 from low adopters, as long as their trends over time are similar (and they are). Placebo analyses further support the assumptions underlying the research design.

4. We use the affiliation of patients and providers in 2019 to avoid endogenous sorting related to telemedicine adoption. While most patients remain with the same provider, we measure outcomes over patient visits with any provider, not just their affiliated one.

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). Additionally, 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 who 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 physicians, 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 led 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 to our baseline analysis, which is reassuring. Further, despite heterogeneity in physician telemedicine adoption, telemedicine impacts are fairly homogeneous across physician groups. Analyses for patient subgroups reveal similar results. Together, these findings suggest that the impacts of telemedicine are fairly general and not driven by any particular subgroup.

The increased probability of follow-ups raises the possibility that physicians are less certain about 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 infection (UTI), heart attack, and bone fracture, which we chose because they are common and, more importantly, 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 abnormal levels of missed diagnoses or adverse outcomes associated with remote care.

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. These findings apply across multiple different patient and physician types. They suggest that providing patients access to telemedicine can productively complement in-person primary care.

It is important to emphasize the specific Israeli institutional setting, which may be particularly well suited for incorporating telemedicine. Because physicians are salaried in Israel, the observed mix of remote and in-person medicine is unlikely to be distorted by financial incentives. It may be more challenging to achieve the proper mix of traditional and remote care using service-level payment schedules or utilization caps, especially given the growing variety of encounter types (including audio, video, and text). In light of this, as we discuss in the end of the paper, telemedicine expansion may strengthen, and perhaps expedite, the ongoing policies that emphasize value-based payment schemes.

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 most 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 that had, in their view, replaced an in-person visit. Shah et al. (2018) also find that virtual visits partly replaced 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. Using data from Sweden from 2012 to 2018, Ellegård, Kjellsson, and Mattisson (2021) also find evidence for only partial substitution. Analyzing commercial claims for 2016–2019, Li et al. (2021) find that telemedicine visits for acute respiratory infection involve more downstream care compared to in-person visits. A meta-analysis by Shigekawa et al. (2018) concludes that the impact of telemedicine interventions on the use of other services remains unclear. Newer work on telemedicine in the era of COVID-19 for the most part describes its utilization. For example, Ziedan, Simon, and Wing (2020) show that state closure policies induced an increase in the use of telehealth modalities; Patel et al. (2021) describe the variation in US telemedicine utilization during the pandemic; and Hatef et al. (2022), using data on commercially insured adults, compare utilization and follow-ups in telemedicine and in-person settings and find that telehealth encounters had higher rates of follow-up and subsequent utilization compared with in-person encounters for minor acute conditions but not for chronic conditions.

Our research design is different from existing works in that we exploit the variation in the recent adoption of telemedicine rather than matching cases across settings to study the impact of telemedicine on care and on care utilization, processes, and outcomes. Given the sharp increase in telemedicine use due to COVID-19, the scale and breadth of our data are 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 cover synchronous visits that are provided, for the most part, by the patient's regular primary care physician, as opposed to asynchronous visits or visits provided by dedicated clinicians in special telemedicine clinics. This nature of broader telemedicine deployment seems more similar to the likely future use of telemedicine in the post-pandemic era. The richness of our data, which include data from EMRs, also helps us explore aspects of care quality that are harder to measure using coarser data.

The rest of the paper proceeds as follows. Section 2 describes the setting and data. Section 3 presents the measurement and patterns in physician adoption of telemedicine. Section 4 discusses our empirical strategy, and Section 5 presents our main results. Section 6 covers additional robustness and heterogeneity analyses, and Section 7 concludes by discussing the potential implications of our results to telemedicine policies.

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 farther than 100 m 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 successfully containing 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 in late April.[5] 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.

5. "IKEA Opens Half of the Stores in Israel after Lockdown Eased." *Reuters*, April 22, 2020.

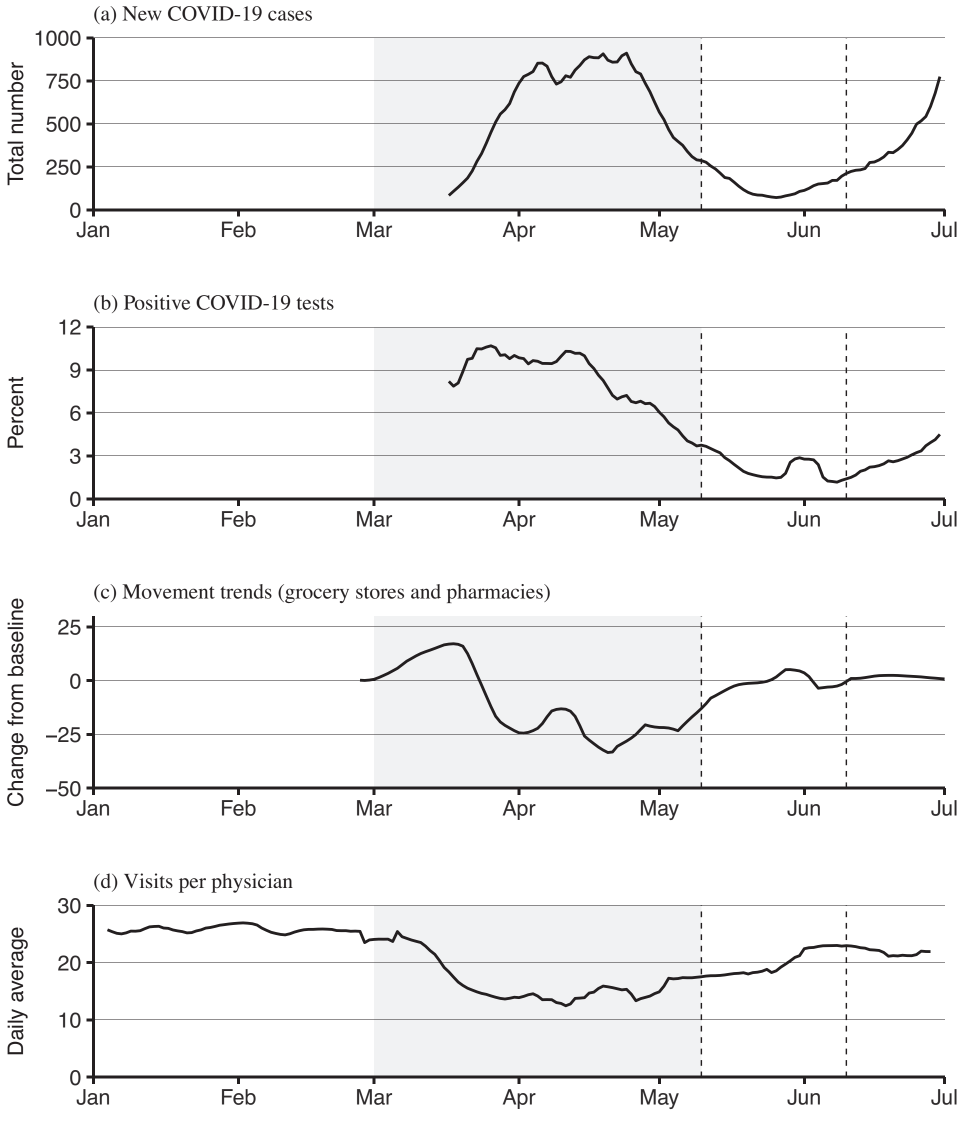


FIGURE 2. The first COVID-19 outbreak in Israel in 2020. Figure shows different statistics around the time of the first COVID-19 wave in Israel in 2020. Gray-shaded areas refer to the lockdown period (March 1–May 10) and the areas between the two vertical dashed lines refer to this study's post-lockdown period (May 11–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 2-day Jewish holiday of Pentecost). Panel c uses data from Google's Global Mobility Report and shows average mobility related to grocery stores 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.

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".[6] Panel c of Figure 2, based on Google Mobility data, shows that visits to grocery stores and pharmacies returned to baseline, pre-COVID levels. Panel d of Figure 2 shows the average daily number of visits to primary care physicians, demonstrating that total visit volumes returned to nearly pre-COVID levels, further supporting the fact that behavior during this period broadly represents the "back to normal" environment and was 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, 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 the low threat of COVID-19.

Guided by this context, we split our sample into three periods.[7] 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. In some of our analyses, we also consider an alternative post-lockdown period starting nearly a year later, from April 5, 2021, to May 30, 2021, when vaccination rates were high and most health emergency restrictions lifted.

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; most of its services are provided by salaried providers, but some services are provided

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

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

by external providers that Clalit reimburses. All four HMOs offer identical coverage but use distinct provider networks, with the exception of hospitals, which are used by all four HMOs. 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 were limited. Service was limited to specialized, after-hours, direct-to-consumer clinics. Physicians did 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.[8]

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 of 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.[9] 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 EMRs data on its patients, which

8. Since 2015, patients could 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.

9. 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.

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 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 Online 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. We also restrict attention to the 90% of Clalit members who had at least one physician visit during the pre-lockdown period, which we use for determining physician affiliation. Online 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 subperiods, 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 to episodes that started during the same date range (May 11–June 7) in 2019. Online 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).[10] 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 the utilization and cost of all services during the 30 days following the index visit. We break down costs into the following categories: prescription drugs, primary care, lab and imaging, specialists, outpatient, ED, inpatient urgent, inpatient elective, and all other services. In our main analysis, we use the following control variables: gender, 5-year age group, the Johns Hopkins Adjusted Clinical Groups (ACG) risk score (a commercial risk classifier that measures predicted future healthcare utilization), number of diagnosed chronic conditions, subdistrict, and category of diagnosis. Online 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 and the rest were in-person visits. Panel A shows data on patient characteristics. Compared to in-person visits, telemedicine visits had patients who (i) were 4 percentage points more likely to be female, (ii) have much higher socioeconomic status (SES), (iii) were more likely to live in urban areas, (iv) were about 3 years older on average, and (v) 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 Online Appendix Figure A.1), further highlighting the need to account for this selection in the study design. Online Appendix Table A.1 shows data on the rates of telemedicine use over time for the same patient groups, showing that these differences also persist over time.

The difference in SES—determined by Israel's Central Bureau of Statistics' classification of the patient's place of residence—is remarkable, with 42% of remote visits being conducted with patients from the top SES tercile, compared with only 26% of in-person visits.[11] It highlights the need to account, as we do, for variation across locations 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% vs. 53.1%), more lab tests (32.4% vs. 30.9%), and fewer referrals to other providers (e.g., 0.5% of remote visits are referred to the ED vs. 0.8% of in-person visits). Panel C

10. During the study period, the exchange rate was approximately 3.6 NIS per USD.

11. Patel et al. (2021) document similar patterns in the United States.

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
Urban	0.469	0.577
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

Notes: 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 7 days following the index visit, with both primary care physicians and specialists. In Panel D, 30-day cost includes the cost of all events that started within 30 days of an index primary care visit.

shows data on the average number of physician visits in the 7-day period after the index visit. Episodes starting with a remote index visit 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 vs. 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 slightly higher total spending on average than episodes starting with an in-person visit (688 NIS compared to 657 NIS).

3. Physician Adoption of Remote Care

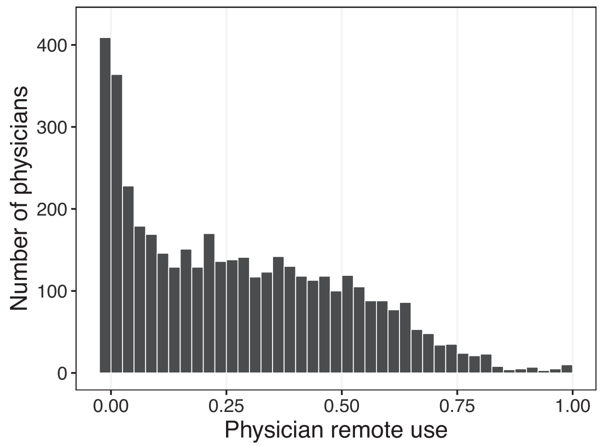
Measuring Physician Adoption. To measure the propensity of each physician to adopt telemedicine, we estimate the following regression using data on all visits conducted by physicians in our sample during the lockdown period:

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

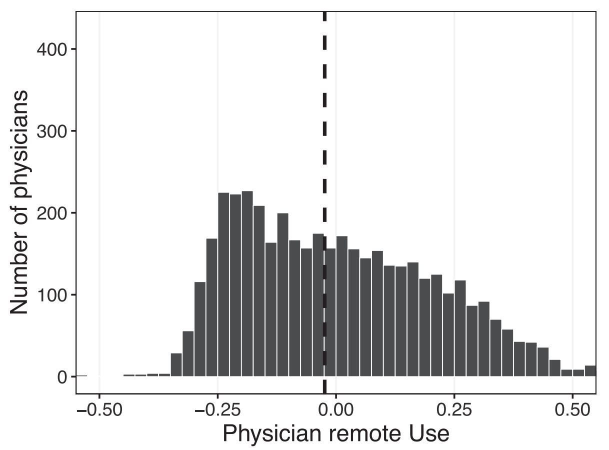
In this specification, i, j, t, and l are indices for the index visit of patient i with physician j at time (week) t and location (subdistrict) l. Remote_{ijtl} is an indicator for a remote visit; X_{it} denotes visit controls, including patient age, gender, number of chronic conditions, ACG score, and diagnosis category; and τ_t and η_l are week and subdistrict fixed effects. The estimated physician fixed effects, α_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 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 0 or very few telemedicine visits, about a sixth shifted the majority of their practice to be remote during the lockdown period. Panel b shows the distribution of estimated physician fixed effects (α_j from equation (1)). Accounting for time, location, and visit characteristics, the tendency of physicians in our sample to adopt telemedicine is more symmetrically distributed around the median of −0.024. We henceforth refer to this estimated α_j as the physician's *telemedicine adoption*. Below, we use it to classify physicians as high or low adopters.

Physician Adoption Is Heterogeneous and Persistent. To explore how adoption correlates with different observed physician characteristics, Table 2 shows the results of regressing our measure of physician adoption, α_j from equation (1), on different physician characteristics. All else being equal, female physicians, younger physicians, more-experienced physicians, and family specialists had a higher tendency to adopt telemedicine during the lockdown period. The starkest difference is by gender: Female physicians' share of remote visits during the lockdown was 12.1 percentage points higher than male physicians' share. Even after adjusting for other physician characteristics, the difference remains at 8.8 percentage points. We also observe experience and age gradients in adoption, with the opposite sign: All else being equal, the share of remote visits by physicians in the top age tercile is 9.3 percentage points lower than that of the youngest physicians. In contrast, more-experienced physicians perform, all else being equal, a greater share of their visits remotely. We also explore whether telemedicine adoption correlates with other features of the physician's (pre-lockdown) practice style. As Table 2 shows, primary care physicians with a higher propensity to use referrals tend to also be those who are more likely to adopt telemedicine, while the correlation of adoption with volume and the propensity to use prescriptions is small.



(a) Raw telemedicine share of visits



(b) Residualized telemedicine share of visits

FIGURE 3. Physician utilization of telemedicine. The 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 0 telemedicine visits; other bins cover left-open right-closed intervals of width 0.025.) 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 (−0.024), which we use to classify physicians as high or low adopters.

Physician telemedicine adoption is also persistent. Online Appendix Figure A.2 shows evidence on the heterogeneity in physician adoption of telemedicine by period and physician characteristics, after adjusting for patient characteristics by residualizing adoption rates using the same controls as in equation (1). Across all

TABLE 2. Telemedicine adoption and physician characteristics.

	Dependent variable:							
	Physician telemedicine adoption							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.121							0.088
	(0.006)							(0.006)
Age (middle tercile)		−0.037						−0.060
		(0.008)						(0.008)
Age (top tercile)		−0.073						−0.093
		(0.008)						(0.009)
Experience (middle tercile)			−0.001					0.022
			(0.008)					(0.008)
Experience (top tercile)			−0.009					0.048
			(0.008)					(0.009)
Family medicine				0.070				0.048
				(0.007)				(0.007)
Volume (middle tercile)					0.035			0.017
					(0.008)			(0.008)
Volume (top tercile)					−0.024			−0.020
					(0.008)			(0.008)
Prescribing (middle tercile)						0.020		0.005
						(0.008)		(0.007)
Prescribing (top tercile)						0.003		−0.004
						(0.008)		(0.007)
Referring (middle tercile)							0.064	0.042
							(0.007)	(0.007)
Referring (top tercile)							0.162	0.113
							(0.007)	(0.008)
R^2	0.086	0.021	0.0004	0.022	0.016	0.002	0.106	0.188

Notes: The table shows the results of regressing our measure of physician propensity to adopt telemedicine during the lockdown period (α_j from equation (1)) on various predetermined physician characteristics, separately and jointly. Female and Age refer to the physician demographic characteristics. Family medicine is an indicator for the physician specializing in family medicine or internal medicine rather than pediatrics. Volume, Prescribing, and Referring refer to the average weekly number of visits, the propensity to prescribe medications, and the propensity to refer patients in the pre-period. The sample consists of 4,293 physicians and its construction is described in detail in Online Appendix A.

these dimensions, adoption patterns are similar between the lockdown and post-lockdown periods, supporting our research design (described in the next section), which uses lockdown adoption as a proxy for later access. For example, after adjusting for case characteristics, female doctors performed 36.4% of their visits remotely during the lockdown period, relative to only 21.6% of visits by male physicians. A similar difference exists during the post-lockdown period (28.7% for female physicians vs. 15.8% for male physicians). The difference remained very similar even during the alternative post period, characterized by widespread vaccinations and minimal COVID-19 restrictions (28.3% for female physicians vs. 16.1% for male physicians).

In all cases, the adjusted rates are also very similar to the rates unadjusted by patient age, gender, risk, and condition, suggesting little sorting of patients into physicians on all of these observed dimensions.

Physician Adoption Is Approximately Unidimensional. A potential concern about our measure of physician adoption, α_j, is that telemedicine adoption is assumed to be unidimensional. However, physicians' propensity to use telemedicine may depend on the patient's characteristics. For example, some physicians may be inclined to use telemedicine with older patients, others may be more inclined to use telemedicine with sicker patients, and some may like the idea of telemedicine across the board.

To evaluate this possible concern, we estimate equation (1) separately for different types of patients, splitting the sample (separately) by gender, at the median age, and at the median ACG risk score. We then estimate α_j for each patient group, constructing a six-dimensional measure of physician adoption of telemedicine. Online Appendix Table A.3 describes the correlations between these estimated tendencies across different patient types. We find an extremely high correlation between physicians' tendency to adopt telemedicine across the six patient types defined by age, gender, and risk. For example, the correlation between physicians' telemedicine adoption for male and female patients is 0.96, the correlation between telemedicine adoption for older and younger patients is 0.92, and the correlation for patients who are above and below the median ACG score is 0.96. This evidence suggests that physician adoption is approximately uniform across patient types.

4. Estimating the Impact of Increased Telemedicine Access

Our primary objective in this paper is to estimate the impact of telemedicine relative to in-person care. Naturally, the choice of a remote versus in-person setting for a primary care visit is likely endogenous. Therefore, our empirical strategy does not rely on directly comparing remote visits to in-person visits. Instead, we take advantage of the fact that pre-existing relationships between patients and their primary care physicians, combined with the ample heterogeneity in physician adoption, produce variation in patients' access to telemedicine during the post-lockdown period. We leverage this variation to study the impact of access to telemedicine on different outcomes measured across all visit settings. This section discusses the empirical strategy, underlying measurements, estimation procedures, and identification assumptions.

4.1. Empirical Strategy

Our empirical strategy consists of two steps. First, based on the measure of adoption discussed in the previous section, we split the patient population into those whose primary care physicians had a high propensity to adopt telemedicine and those whose primary care physicians had a low adoption propensity during the lockdown period. Second, to account for potentially unobserved differences between the patient populations of high- and low-telemedicine physicians, we apply a difference-in-differences strategy using data on the pre-lockdown period.

In the first step, we classify physicians as high-telemedicine adopters based on whether their estimated α_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.[12] 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.

Online Appendix Table A.4 presents summary statistics on the characteristics of high and low adopters and their case mix during the post-lockdown period. Panel A shows data on the characteristics of physicians, revealing similar patterns to those observed in Table 2 and discussed in Section 3. That is, compared with low adopters, high-telemedicine adopters are more likely to be female, somewhat younger, and more likely to specialize in family medicine than in pediatric medicine. 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 SES and are more likely to be female. These differences highlight the need to account for differences in characteristics and case mix between high and low adopters and their patients.

The persistence of both patient-provider relationships and telemedicine adoption by physicians supports our use of physician lockdown adoption as a proxy for their patient's post-lockdown use of telemedicine. Patients affiliated with high-telemedicine physician adopters conducted 30% of their post-lockdown primary care visits with any primary care physician remotely, compared to 8% for patients affiliated with low adopters.

As discussed in Section 3, physician adoption of telemedicine, which we use as a proxy for patient access, is correlated with other features of the physicians. It is also natural that different physician groups have different baseline practice styles. Hence, to separately identify the impacts of telemedicine from these baseline differences between physicians, we use a difference-in-differences approach that compares post-lockdown

12. In Section 6.1, we check the robustness of our results to this measure by reproducing all findings using alternative measures of telemedicine access that instead of splitting physician adoption at the median, compare the top and bottom terciles or quartiles of adopters.

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, in the second step of our strategy, 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; $\mu_{j(i)}$, ζ_t, and $\omega_{l(i)}$ are physician, week, and subdistrict fixed effects; and X_{it} are visit controls. The parameter of interest is β, which captures the impact of access to telemedicine. It is estimated as the difference-in-differences in the outcome 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).

4.2. Potential Concerns

The key identification assumption is that if not for the impact of telemedicine, high- and low-telemedicine adopters would have had similar trends in their medical practice, and their patients would have had 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 7-day physician follow-ups are shown in Online Appendix Figures A.2 and A.3). 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

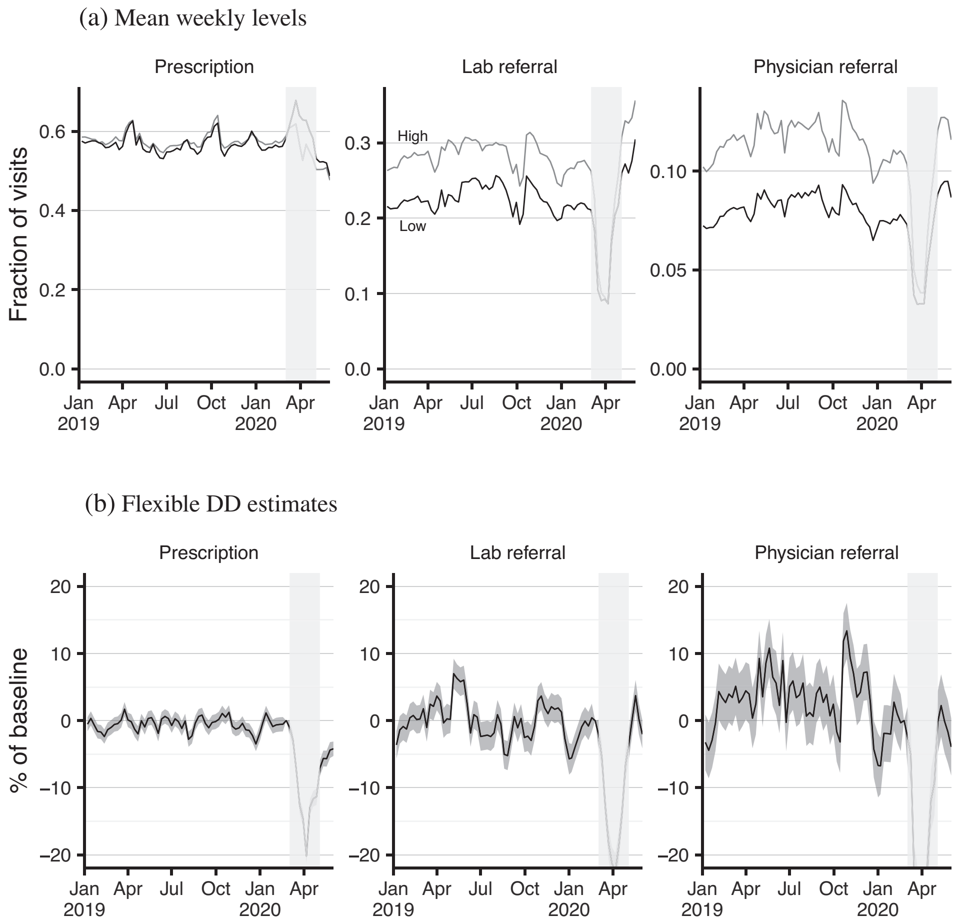


FIGURE 4. Flexibly estimated time trends in common visit outcomes, by physician telemedicine use during the lockdown period. The figure shows, using the sample of all visits starting new primary care episodes, flexibly estimated time trends for the three most common visit outcomes. Panel a shows raw (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 indicators, and the same week indicators interacted with an indicator for High. The figure shows the estimates of the interacted week indicators (week × 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.

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 accessing their physician during the lockdown period. Thus, they may have been more likely to defer care and had differentially more pent-up demand post lockdown. We explore this concern by repeating our analysis, focusing on medical conditions that are less likely to be deferrable.

A different, more standard concern is one of reverse causality. Namely, the concern is 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 described 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 Online 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. This helps guarantee that a potentially differential tendency to switch primary care physicians during the post-lockdown period does not confound our results. We also report below (in Section 6.1) reassuring results from auxiliary analyses in which we use "placebo" post periods (from before telemedicine adoption).

5. Results

5.1. 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.[13] 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

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

TABLE 3. The impact of telemedicine on utilization and total cost of care.

	Pre-lockdown mean (1)	Estimated impact (2)	(S.E.) (3)	Percentage impact (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%

Notes: The table shows the estimated impacts of increased access to telemedicine on utilization and total cost of care. Each row shows an estimate of β 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 post-period 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.

further explore—and confirm—this hypothesis in the next section), suggesting that the marginal increase in utilization is coming from cases that are less severe.

5.2. *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 (i.e. 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 percentage 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 ED (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 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.

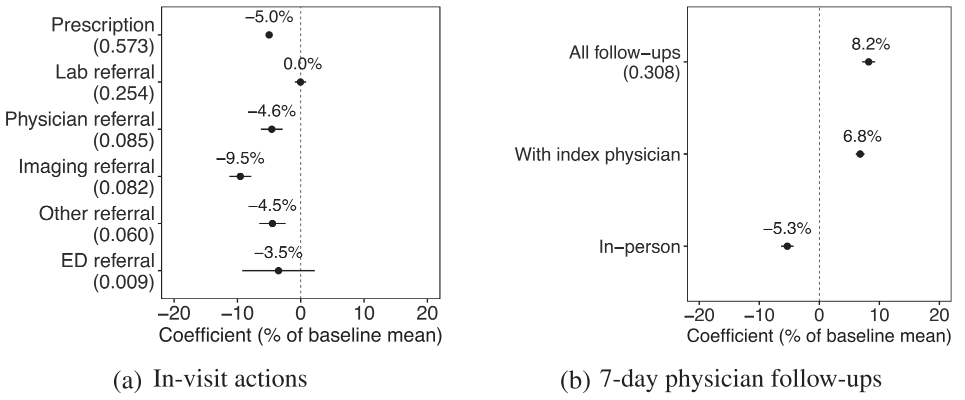
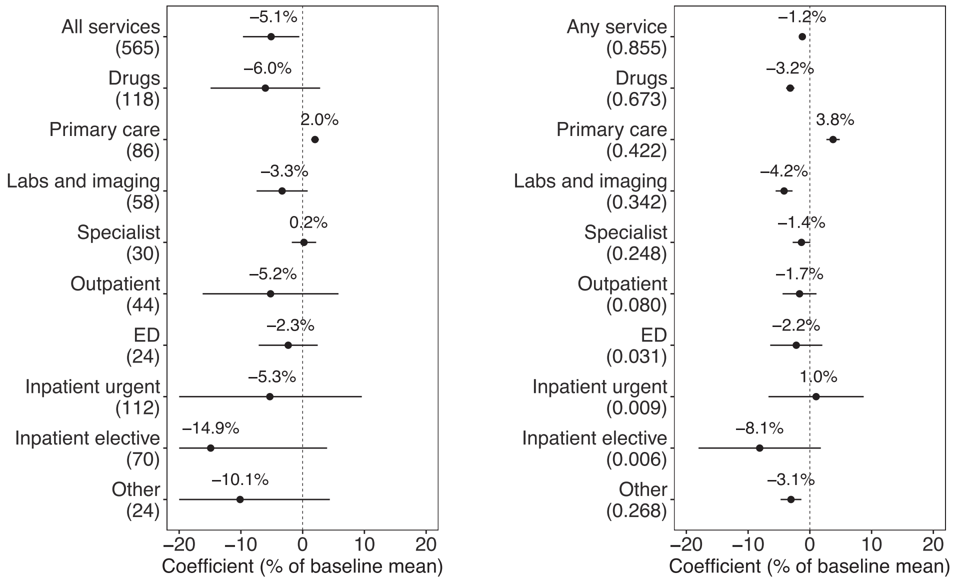


FIGURE 5. The impact of increased access to telemedicine on index visit in-visit actions and 7-day follow-ups. The figure shows the estimated impacts of increased access to telemedicine on visit outcomes. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine (β 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 parentheses). In Panel b, all coefficients are represented as a percent of the mean of all follow-ups (0.308). Online Appendix Table A.9 (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.

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 an 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. However, 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



(a) Cost (b) Utilization

FIGURE 6. The impact of increased access to telemedicine on cost and utilization 30 days after an index primary care visit. The figure shows the estimated impacts of increased access to telemedicine cost and utilization. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine (β 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 parentheses). Panel a shows estimates for the average cost of services by type of service. Costs include 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). Online Appendix Table A.9 (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.

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.

5.3. *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. However, 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: UTI, acute myocardial infarction (AMI, also known as "heart attack"), and bone fracture.

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). Online Appendix Tables A.5, A.6, and A.7 show the respective lists of target and differential diagnoses that were included in each subsample. Online 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 infections 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, then aggravating symptoms would likely cause 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.[14]

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 UTIs, we control for the patient history of UTIs (a risk factor) and consider as outcomes referrals to urine tests (the most common diagnostic test) and antibiotics specific to UTIs (the main treatment). Online Appendix Table A.8 shows detailed summary statistics that specify all risk factors, diagnostics, and outcomes we use for each of the subsamples, which are further discussed in Online Appendix B. One 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

14. A similar idea is used in Abaluck et al. (2016), Mullainathan and Obermeyer (2019), and Chan, Gentzkow, and Yu (2019).

TABLE 4. The impact of telemedicine on the diagnosis of specific medical conditions.

	UTI				AMI				Fracture			
	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%

Notes: The table shows estimates of the impact of access to telemedicine (β from the model specified in equation (2)), for subsamples of specific conditions and their differential diagnoses. The samples are described in detail in Section 5.3. 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 fracture. Prescriptions refer to specific antibiotics for UTI, aspirin and nitroglycerin for AMI, and opioids for fracture. Section 5.3 and Online Appendix B describe the sample construction, variable definitions, and empirical specifications in detail.

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 fracture. 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.

6. Heterogeneity and Robustness

6.1. 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, 2019, and February 7, 2019. The post period is between January 11, 2020, 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 had not yet occurred by February 2020, under the identification assumptions, we expect to find no difference between high and low adoption groups. Online Appendix Figure A.4 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 a complete reopening of the economy. Descriptive statistics and further details on the context are discussed in Online Appendix D, and the results from this alternative specification are reported in Panel A of Table 5 and Online Appendix Figure A.5.

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 follow-ups (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 reproduce all findings using two alternative measures of telemedicine adoption. First, we categorized patients as having high or low access based on whether their physicians' estimated tendency to use telemedicine (represented by α_j in equation (1)) fell within the top or bottom tercile, excluding physicians in the middle tercile. Secondly, we use a similar measure, comparing the top and bottom quartiles instead. We also estimate a more flexible version of equation (2), in which we interact β with an indicator for the decile of α_j from equation (2). Key results are reported in Panel A of Table 5 and Online Appendix Figure A.6, and full results are reported in Online Appendix Figure A.7. Results are similar to the ones obtained using our original measure of adoption.

Deferrability of the Index Condition. As discussed in Section 4, an important plausible concern about our empirical strategy is that low-access patients might have

TABLE 5. Robustness.

	Index-visit and episode outcomes					Overall Cost and Use			
	Prescription (1)	Lab referral (2)	All follow-ups (3)	30-day cost (4)	30-day utilization (5)	Total cost of primary care episodes (6)	Any primary care episodes (7)	Total healthcare cost (8)	Any healthcare utilization (9)
A. Specification									
Main specification	−5.0%	0.0%	8.2%	−5.1%	−1.2%	−5.7%	3.5%	−3.0%	0.3%
	(0.2%)	(0.5%)	(0.6%)	(2.3%)	(0.2%)	(1.9%)	(0.3%)	(1.5%)	(0.1%)
Alternative post period	−4.4%	−1.1%	2.4%	1.8%	−1.0%	−5.4%	3.5%	−3.6%	1.2%
	(0.4%)	(0.7%)	(0.7%)	(2.8%)	(0.2%)	(2.6%)	(0.2%)	(1.4%)	(0.1%)
Alternative access measures:									
Top vs. bottom tercile	−6.1%	−0.1%	11.0%	−3.2%	−1.2%	−5.6%	5.5%	−4.4%	0.5%
	(0.5%)	(1.1%)	(0.9%)	(2.7%)	(0.2%)	(2.8%)	(0.3%)	(1.9%)	(0.2%)
Top vs. bottom quartile	−7.4%	0.8%	12.4%	−0.5%	−1.5%	−3.6%	6.7%	−4.5%	0.8%
	(0.6%)	(1.2%)	(1.1%)	(3.2%)	(0.2%)	(2.7%)	(0.4%)	(2.3%)	(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%)		

Notes: The table shows estimates and standard errors (in parentheses) of the impact of access to telemedicine (β from the model specified in equation (2)) for different key outcomes (in columns) and different specifications (in rows). Estimates are scaled as a percent of each outcome's pre-lockdown mean. 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 and quartiles 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, separately for outcomes of index visits that are more or less deferrable, based on the diagnosis. We consider diagnoses with an above-median drop during lockdown as more deferrable and the rest as less deferrable. Online Appendix C discusses the details of the deferrability definition and sample construction. Results for total healthcare cost and use are not reported because these outcomes are not tied to a specific visit, which is the basis of our classification of deferrability. Section 6 and Online Appendix A discuss in detail the sample and variable definitions.

been more likely to defer care during the lockdown period and consequently have greater pent-up demand for care post lockdown.[15] 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 the lockdown as more deferrable and the rest as less deferrable. Online 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 prescriptions 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. Figure 7 show results for all other outcomes. Overall, the estimated impacts of telemedicine are fairly similar between these two groups of conditions.

6.2. *Heterogeneity across Patients and Physicians*

Our large sample size allows us to explore further the heterogeneity in our key estimates across different subsamples. We analyze the heterogeneity of our main estimates by repeating our main analyses separately for different subsamples by patient age, gender, SES, and place of residence urbanicity.[16] These estimates for the impact of access to telemedicine on visit outcomes of different subgroups are summarized in Table 6 and presented in detail in Online Appendix Figures A.8–A.11. Naturally, when we focus on smaller subsamples, estimates are noisier and statistical power is more limited. However, overall, despite the differences in baseline outcomes across the different age, gender, and SES subgroups, estimates of the impact of telemedicine relative to

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

16. For age, we break the sample into three age groups: children (aged 0–18), adults (aged 19–64), 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's place of residence (see Online Appendix A). For urbanicity, we break the sample at the median population density at the patient's place of residence.

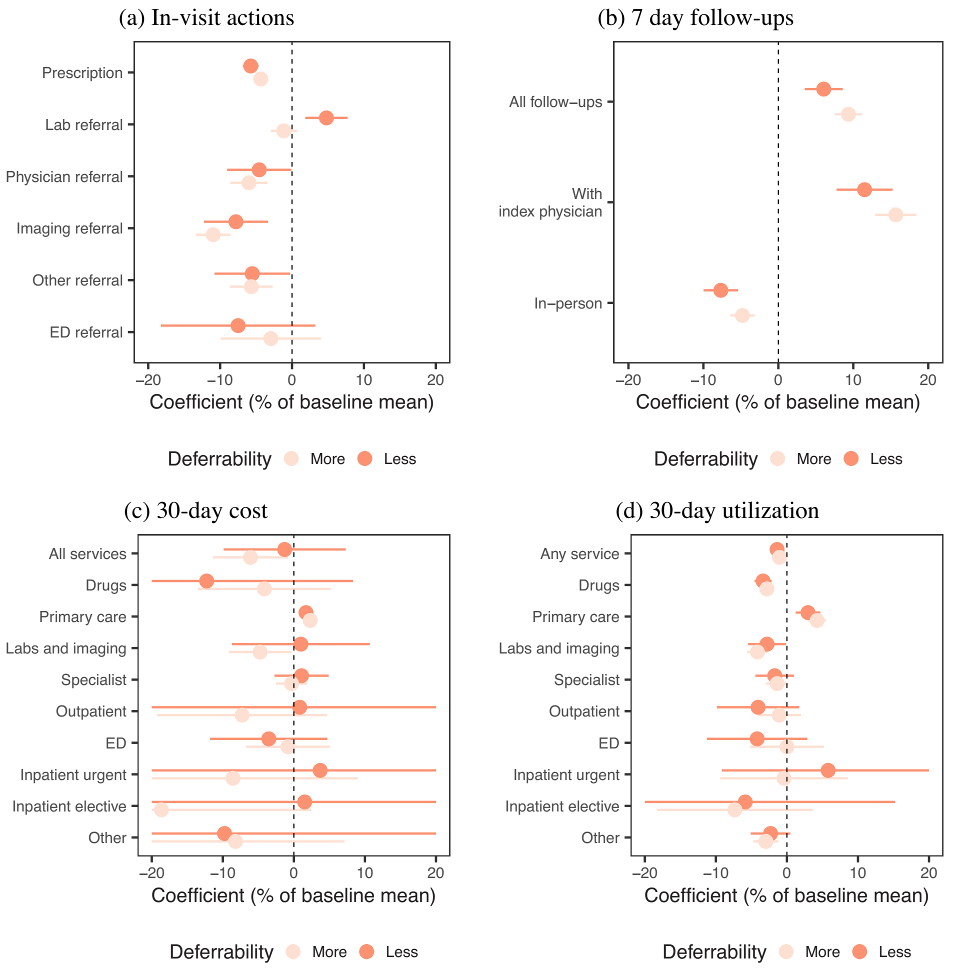


FIGURE 7. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30- day cost and utilization, by deferrability of diagnoses. The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by the deferrability of the medical diagnosis associated with the index visit (see legend). The sample includes all new primary care episodes. Each row shows an estimate β 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 6.1 discusses in more detail the sample and variable definitions.

TABLE 6. Heterogeneity by patient characteristics.

	Index-visit and episode outcomes					Overall cost and use			
	Prescription (1)	Lab referral (2)	All follow-ups (3)	30-day cost (4)	30-day utilization (5)	Total cost of primary care episodes (6)	Any primary care episodes (7)	Total healthcare cost (8)	Any healthcare utilization (9)
A. Age group									
Child (0–18)	−3.2% (0.7%)	−7.1% (1.9%)	10.9% (1.7%)	−9.6% (4.8%)	−1.2% (0.4%)	−3.4% (5.2%)	1.2% (0.5%)	−6.3% (5.0%)	−0.8% (0.3%)
Adult (19–64)	−7.0% (0.5%)	−0.4% (1.0%)	7.1% (1.0%)	−8.9% (3.4%)	−1.8% (0.2%)	−9.3% (3.1%)	0.1% (0.4%)	−3.1% (1.9%)	−1.1% (0.2%)
Senior (65+)	−2.5% (0.5%)	1.7% (1.2%)	6.3% (1.4%)	0.1% (4.1%)	−0.1% (0.2%)	−6.1% (3.6%)	−3.8% (0.8%)	0.1% (2.1%)	−1.3% (0.2%)
B. Gender									
Male	−4.2% (0.5%)	−0.2% (1.1%)	9.3% (1.1%)	−4.4% (3.8%)	−0.9% (0.3%)	−7.5% (3.7%)	3.4% (0.4%)	−2.9% (2.1%)	0.4% (0.2%)
Female	−5.7% (0.4%)	0.1% (0.9%)	7.3% (0.9%)	−5.8% (2.8%)	−1.5% (0.2%)	−3.7% (2.8%)	3.6% (0.4%)	−2.8% (1.7%)	0.1% (0.2%)
C. Socioeconomic status									
Low	−3.0% (0.7%)	0.8% (1.7%)	3.8% (1.5%)	−15.4% (4.8%)	−1.1% (0.3%)	−14.4% (5.2%)	−1.5% (0.6%)	−3.9% (2.8%)	−1.5% (0.3%)
Medium	−3.8% (0.5%)	−2.6% (1.3%)	8.7% (1.2%)	4.6% (3.6%)	−0.8% (0.3%)	6.8% (3.4%)	7.7% (0.5%)	−1.1% (2.2%)	1.6% (0.2%)
High	−4.1% (0.6%)	−3.3% (1.2%)	8.3% (1.3%)	−3.5% (4.2%)	−0.6% (0.3%)	−0.9% (3.6%)	7.2% (0.5%)	−1.5% (2.4%)	1.8% (0.2%)
D. Population density									
Rural	−5.0% (0.5%)	1.9% (1.2%)	7.2% (1.0%)	−6.2% (3.7%)	−1.6% (0.3%)	−8.7% (3.4%)	0.8% (0.4%)	−5.1% (2.3%)	−0.5% (0.2%)
Urban	−4.1% (0.5%)	−1.6% (1.1%)	7.6% (1.1%)	−5.0% (3.3%)	−0.7% (0.2%)	−3.1% (2.9%)	6.5% (0.4%)	0.1% (1.9%)	1.5% (0.2%)

Notes: The table shows estimates and standard errors (in parentheses) of the impact of access to telemedicine (β from the model specified in equation (2)) for different key outcomes (in columns) and different specifications (in rows). Estimates are scaled as a percent of each outcome's pre-lockdown mean. Results in each panel repeat our main analyses separately for different subsamples defined by the patient's age group, gender, tercile of socioeconomic rank (defined based on the average income at the patient place of residence), and urbanicity of the patient place of residence. Section 6 and Online Appendix A discuss in detail the sample and variable definitions.

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.

To analyze the heterogeneity of our main estimates by physician type, we repeat our main analyses separately for different subsamples defined by each patient's primary care physician in the pre-period. We analyze heterogeneity by physician gender, age, experience, specialty, and pre-period practice characteristics (patient volume, prescribing propensity, and referral propensity; Online Appendix A discusses in detail the definitions of these measures). These estimates for the impact of access to telemedicine on key outcomes for different physician groups are summarized in Table 7. Detailed results are presented in Online Appendix Figures A.12–A.16. The impacts of telemedicine access on primary care utilization are slightly higher for patients whose main primary care physician (pre-pandemic) was female, had a low volume of patients, or had a higher-than-average tendency to refer patients. The (negative) impact of telemedicine adoption on prescriptions is somewhat stronger among patients of high prescribers. However, despite the documented heterogeneity in adoption by different physician groups (discussed in Section 3), most results do not point to substantial heterogeneity in telemedicine impacts across different physician types.

7. Potential Implications to Policy Discussions around the World

As we discussed in Section 1, telemedicine entails both risks and opportunities. On the one hand, telemedicine can improve access to care, make receiving care much more convenient, expand the geographic reach of providers, and facilitate better continuity of care. On the other hand, the ease of provision of and access to telemedicine might lead to excessive and low-value utilization. Further, remote diagnosis without physical examination of patients could lower the quality of diagnosis and treatment.

Indeed, these pros and cons of telemedicine have dominated the policy discussions in the post-pandemic era, with policymakers around the world trying to find the appropriate balance. The expanded use of telemedicine during the pandemic made it clear that going back to pre-pandemic, minimal use of telemedicine is unrealistic and unwise. Yet, concerns regarding the overuse of telemedicine have dominated the policy discussion, especially when regulators have tried to fit telemedicine payment policies into the pre-existing and familiar framework of in-person medicine.

Concerns regarding overuse are particularly strong in countries such as Australia, Belgium, Denmark, France, Germany, the Netherlands, Canada, Switzerland, and the United States, where telemedicine is reimbursed on some form of a fee-for-service basis, which may skew provider incentives. In the United States, for example, this concern has led to an ongoing debate about the appropriate fee structure for telemedicine, with a particular focus on telemedicine payment parity; that is, the requirement that payers should reimburse remote encounters at the same rate as

TABLE 7. Heterogeneity by physician characteristics.

	Index-visit and episode outcomes					Overall cost and use			
	Prescription (1)	Lab referral (2)	All follow-ups (3)	30-day cost (4)	30-day utilization (5)	Total cost of primary care episodes (6)	Any primary care episodes (7)	Total healthcare cost (8)	Any healthcare utilization (9)
A. Gender									
Female	–4.0%	–2.8%	7.9%	–4.8%	–0.6%	–1.6%	8.6%	–1.5%	2.0%
	(0.6%)	(1.2%)	(1.3%)	(3.6%)	(0.3%)	(3.7%)	(0.5%)	(1.9%)	(0.2%)
Male	–3.7%	0.4%	6.1%	–3.2%	–1.0%	–4.8%	2.1%	–2.1%	0.2%
	(0.5%)	(1.2%)	(1.1%)	(3.3%)	(0.3%)	(2.9%)	(0.4%)	(2.1%)	(0.2%)
B. Age tercile									
Bottom	–5.5%	1.2%	7.7%	–12.4%	–0.8%	–5.3%	2.4%	1.0%	–0.7%
	(0.7%)	(1.7%)	(1.5%)	(4.6%)	(0.3%)	(4.3%)	(0.6%)	(2.4%)	(0.2%)
Top	–4.4%	–2.4%	7.7%	–5.1%	–1.2%	–6.0%	4.0%	–3.8%	0.7%
	(0.7%)	(1.5%)	(1.4%)	(4.3%)	(0.3%)	(3.6%)	(0.5%)	(2.1%)	(0.2%)
C. Experience tercile									
Bottom	–4.2%	1.9%	7.9%	–15.9%	–0.8%	–10.3%	2.0%	0.0%	0.5%
	(0.8%)	(1.7%)	(1.8%)	(4.9%)	(0.4%)	(4.4%)	(0.6%)	(2.6%)	(0.2%)
Top	–5.6%	–0.3%	8.3%	–3.1%	–1.7%	–8.6%	3.4%	–3.8%	0.0%
	(0.6%)	(1.4%)	(1.3%)	(4.0%)	(0.3%)	(3.5%)	(0.5%)	(2.0%)	(0.2%)
D. Specialty									
Pediatrician	–2.9%	–6.0%	9.6%	–10.0%	–0.9%	–6.2%	–0.2%	–1.6%	–1.8%
	(0.8%)	(2.0%)	(1.8%)	(4.9%)	(0.4%)	(4.4%)	(0.5%)	(3.9%)	(0.2%)
Family	–5.9%	1.5%	7.0%	–5.9%	–1.4%	–6.9%	2.1%	–3.2%	–0.4%
	(0.5%)	(1.0%)	(0.9%)	(2.7%)	(0.2%)	(2.5%)	(0.4%)	(1.4%)	(0.1%)
E. Case volume									
Low activity	–6.4%	–5.1%	9.0%	–9.7%	–1.4%	7.2%	8.3%	–2.3%	3.4%
	(1.2%)	(2.8%)	(2.6%)	(8.4%)	(0.6%)	(11.4%)	(1.3%)	(5.1%)	(0.6%)
High activity	–4.5%	0.6%	7.1%	–5.9%	–1.1%	–6.6%	2.2%	–2.6%	0.0%
	(0.5%)	(1.1%)	(1.0%)	(2.9%)	(0.2%)	(2.8%)	(0.4%)	(2.0%)	(0.2%)

TABLE 7. Continued.

	Index-visit and episode outcomes					Overall cost and use			
	Prescription (1)	Lab referral (2)	All follow-ups (3)	30-day cost (4)	30-day utilization (5)	Total cost of primary care episodes (6)	Any primary care episodes (7)	Total healthcare cost (8)	Any healthcare utilization (9)
F. Prescribing propensity									
Low prescriber	−7.1%	−3.6%	10.7%	−6.1%	−0.8%	−4.3%	2.1%	0.3%	−0.1%
	(1.2%)	(1.6%)	(1.8%)	(4.4%)	(0.4%)	(4.0%)	(0.5%)	(2.4%)	(0.2%)
High prescriber	−12.3%	2.7%	8.8%	−9.4%	−1.3%	−7.4%	3.3%	−6.0%	0.5%
	(1.4%)	(1.4%)	(1.6%)	(4.5%)	(0.3%)	(3.9%)	(0.5%)	(2.1%)	(0.2%)
G. Referral propensity									
Low referrer	−7.1%	0.0%	11.5%	−11.8%	−0.9%	−7.7%	−2.8%	−4.4%	−2.1%
	(1.4%)	(2.1%)	(2.5%)	(5.2%)	(0.4%)	(5.6%)	(0.5%)	(3.2%)	(0.2%)
High referrer	−7.6%	−0.6%	6.4%	−6.2%	−0.6%	−1.1%	7.4%	0.7%	1.5%
	(1.2%)	(1.2%)	(1.3%)	(4.0%)	(0.3%)	(3.4%)	(0.6%)	(1.7%)	(0.2%)

Notes: The table shows estimates and standard errors (in parentheses) of the impact of access to telemedicine (β from the model specified in equation (2)) for different key outcomes (in columns) and different specifications (in rows). Estimates are scaled as a percent of each outcome's pre-lockdown mean. Each panel summarizes the results for different subsamples defined by the characteristics of the patient's main (pre-pandemic) primary care physician. Volume, prescribing, and referral propensity are measured during the pre-period. Prescribing and referral propensities are residualized by case characteristics. Section 6 and Online Appendix A discuss in detail the sample and variable definitions.

in-person ones.[17] Other countries have experimented with other regulations that put direct caps on utilization rather than pay. For example, Germany only pays for one remote visit per episode of care and has a 30% cap (up from 20% before the pandemic) on the share of remote visits each provider can be paid for. Belgium caps the number of reimbursable remote visits at five per physician–patient pair for each 30-day period, and Australia reimburses specialist video consults only for patients living more than 15 km away.

The Israeli setting, like that of other countries, such as the United Kingdom and Sweden, is quite different. Physicians are salaried, so service-level payment parities are less relevant, and provider-side incentives to overuse telemedicine are not as central. Therefore, the observed mix of remote and in-person medicine is less distorted by financial and non-medical incentives.

Consistent with this aspect of the Israeli setting, our general findings are best viewed as a "proof of concept". They illustrate that telemedicine use can expand massively without detectable adverse effects. Specifically, we do not find any evidence of diagnostic inaccuracy in remote visits for specific conditions. We find a relatively small impact on overall utilization, a (small) negative impact on costs, and an increase in follow-up care. These results hold across multiple patient and physician groups. Further, these results do not account for other non-monetary costs of care, such as travel costs and wait times, that telemedicine reduces.[18]

These findings suggest that—with an appropriate handle on physician incentives—there is real value in incorporating and expanding remote medicine and making it an important and integral part of the mix of healthcare services. Controlling physician incentives would surely be a challenge. Regulators would have to recognize that telemedicine is a new (complementary) approach to patient care. It may require new payment models rather than an attempt to fit it into payment policies developed in the era of fully in-person care. That is, instead of utilization caps or payment schedules that would compare remote visits (or phone calls or text messages) to an in-person visit, regulators, payors, and health systems around the world might be better off focusing on paying for the overall mix of patient care. The trend toward value-based medicine, in which providers are rewarded for patient outcomes rather than inputs, is not new (Porter and Teisberg 2006; HHS 2019). Our findings about the impact of telemedicine

17. During the height of the pandemic and the declaration of a public health emergency, both public and private US insurers, including Medicare, extended telemedicine coverage and initiated payment parity, including for audio-only visits. However, in many cases, these measures were in effect as part of the public health emergency, and many were or are set to be rolled back without more permanent legislation. As of February 2022, 19 state policies require private insurers to implement payment parity, 4 states have payment parity policies with caveats, and 27 states have no payment parity. Even in states with payment parity laws, the legislation varies by what and how much is covered. See "Current Payment Parity Status: The Center for Connected Health Policy", https://www.cchpca.org/, accessed January 2023.

18. By some estimates, accessing professional health care services in the United States required on average 34 min of travel and 11 min of waiting (Rhyan 2022), with an annual opportunity cost of $89 billion. Travel costs are even higher in rural areas (Kornelsen et al. 2021).

suggest that telemedicine would (or at least should) expedite this trend in the context of primary care.

Finally, we should emphasize some limitations to our results. First, they reflect the sorting of patients 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. Therefore, more work would be needed to establish the impact of different factors on the success of remote care provision. Second, because our empirical strategy uses the patients' past affiliation with a primary care physician for the measurement of telemedicine access, it focuses on how telemedicine, once adopted, affects an engaged patient population and not on how the extensive-margin decision to begin seeing a primary care physician may change with the availability of telemedicine. Third, our horizon is relatively short, and more work would be required to assess the longer-term consequences of shifting healthcare to remote settings, such as 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 in healthcare delivery. Avenues for further research include 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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Supplementary Data

Supplementary data are available at *JEEA* online.

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