On-Line Supplementary Appendices

The Impact of Increased Access to Telemedicine

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Appendix A: Sample and Variable Definitions

A.1. Construction of the Main Sample

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

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

Physician–Patient Affiliation. We sample all patients affiliated with any one of these 4,293 active physicians. We consider a physician to be the main primary care provider of a patient if the patient saw this physician the most times in the pre-lockdown period (January 2019 through February 2020).[19] If

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

the patient visited multiple doctors the same (maximal) number of times, we pick as the primary provider the physician whom the patient saw last during that period. We exclude from the sample 10% of Clalit members who had no physician visits throughout the pre-lockdown period, for whom affiliation thus defined is indeterminate. These excluded members account for only 2% of total baseline cost of services. This sample has 4.313 million patients.

Primary Care Episodes. For each sampled patient, we extract all primary care visits that occurred during the study period of January 7, 2019, to June 7, 2020, either in person or remotely. Our focus is new primary care episodes, so we exclude visits that had any encounters with physicians, hospitals, or labs during the 14-day period preceding the visit because such visits likely reflect follow-up encounters that are part of an ongoing episode. The remaining non–follow-up visits account for 44% of all visits. We refer to each one of these (new) visits as the *index* visit of a care episode and attribute all services utilized in the 30-day period subsequent to this index visit to this episode. For consistency across our different analyses, we include in our main sample only episodes that had non-missing control variables (the list of which is described below), resulting in the exclusion of a small number of observations that missed one or more covariates. The resulting sample consists of 12.198 million primary care episodes involving 3.655 million unique patients. This excludes 0.4 million members who, during the study period, did not have any new primary care episodes.

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

A.2. Construction of Additional Samples

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

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

A.3. Variable Definitions

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

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

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

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

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

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

The patient age is the patient five-year age group at the time of the visit. ACG concurrent weight is a risk score that is calculated on a quarterly basis using a commercial classifier.[20] We exclude 2% of episodes with missing ACG scores. Chronic condition counts are based on indicators for 123 chronic condition obtained from a database maintained by Clalit. The ten most common conditions are hyperlipidemia, smoking (as documented in EMR; smoking is a health behavior that is predictive of future healthcare utilization and spending and is thus treated for this purpose like a chronic condition), hypertension, obesity, arthropathy, diabetes, malignancy, ischemic heart disease, arrhythmia, and asthma. The visit location is observed at the level of subdistrict, an administrative division of Israel into 70 geographic areas, each with a similar number of covered members. To determine the diagnostic category of a visit, we group the first diagnosis code of each visit into one of the following 16 diagnosis categories: mental health; endocrine, immune, or lymphatic; urinary/renal; reproductive; brain/neurological; dental;

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

administrative; heart and blood vessels; digestive; respiratory; muscles and skeleton; ear, nose, and throat; eyes; skin; injury/wound/trauma; and other. The association between diagnoses and categories was determined by uploading the English description of the 500 most common diagnoses, which together cover over 90% of cases in our sample, to multiple Amazon Mechanical Turk workers who were asked to classify them, based on Google searches, to the most appropriate category. In case of a disagreement, the most commonly selected category was assigned. We exclude the 8.5% of cases with no associated diagnostic category.

In descriptive analysis and when analyzing heterogeneity, we also use the patient socioeconomic status (SES) and urbanicity. SES is calculated based on the Israel Central Bureau of Statistics socioeconomic classification of the patient municipality of residence. These classifications are based on national income tax records. Urbanicity is defined by merging data on population density (population per square kilometer) of statistical geographic units (which have an average of 2,700 residents) into our data on the address of the members. We are able to provide a measure of population density for over 90% of the sample. We leave out of the relevant analyses the remaining 8.3% for which population density is missing. We define a member as a resident of an urban area if their population density is above the median of 4,500 residents per square kilometer, and rural otherwise.

Physician Characteristics. To study the heterogeneity in the impact of telemedicine adoption across physician groups, we use both directly observed physician characteristics and constructed measures of physicians' clinical behavior. We observe physicians' gender, age, specialty (family medicine or pediatrics), and years in practice at Clalit. We divide the sample by physician experience terciles and age terciles (with cutoffs at 7 and 21 years of experience and at 47 and 61 years of age).

We calculate three additional measures of physician practice. The first is case volume, defined as the number of cases in the pre-lockdown period. We divide the sample into three equal-sized groups by volume, splitting at 2,647 and 6,785 cases. That is, we classify as Low Activity physicians those who conducted less than 2,647 visits in the pre-lockdown period and High Activity physicians those who conducted more than 6,785 visits in the pre-lockdown period. To calculate prescribing and referral propensities of physicians, we estimate a variant of equation (1) using the sample consisting of all pre-period visits, and using as the outcome an indicator for a prescription or a referral (to a lab, specialist, emergency room, or imaging) made by the physician during the visit. In a way analogous to how we define telemedicine adoption, we use physician fixed effects from these variants of equation (1) as our measure of each physician's propensity to prescribe or refer. We then split the sample of physicians into three equally sized groups based on these propensities.

Appendix B: Sample and Variables Used for Analyzing Diagnostic Accuracy

Sample Construction

To evaluate the impact of telemedicine on diagnostic accuracy, we analyze the diagnostic process of three medical conditions: urinary tract infection (UTI), acute myocardial infarction (AMI), and bone fracture. UTI is an infection in any part of the urinary system—kidneys, ureters, bladder, or urethra. Most infections involve the lower urinary tract—the bladder and the urethra. An infection limited to the bladder can be (just) painful and annoying, whereas a UTI that spreads to the kidneys can result in serious complications. A urine test is commonly used to diagnose a UTI. Antibiotics are usually the first line treatment.[21] AMI, a potentially fatal condition, occurs when the flow of blood to the heart is blocked. Although some heart attacks strike suddenly, many people have warning signs and symptoms hours, days, or weeks in advance,

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

and some people who have heart attacks have only mild symptoms. The first diagnostic test for AMI is an electrocardiogram (ECG).[22] Fractures—broken bones—are caused mainly by trauma or osteoporosis (a disorder that involves a reduction in bone density) and are commonly diagnosed using X-ray imaging. Common treatments for fracture include immobilization and pain management.

To account for the endogeneity of the diagnosis itself—particularly for the possibility that physicians may be less accurate in remote settings—we sample each target condition with all related conditions that share similar symptoms and are therefore part of its differential diagnosis. In consultation with a Clalit physician with clinical experience in family medicine, we created a list of all differential diagnoses associated with each target condition. Appendix Table A.5, through Appendix Table A.7 show the respective lists of target and differential diagnoses used in the construction of each sample. For brevity, we refer to these samples by the name of the target condition (e.g., the UTI sample refers to the sample of UTIs and all related differential diagnoses).

For each set of target condition and related differential diagnoses, we sample all non–follow-up primary care visits that occurred between May 11, 2019, and June 7, 2019, and between May 11, 2020, and June 7, 2020 for which the physician recorded at least one of the diagnoses in the visit summary. If members had multiple such visits in the pre- or post-lockdown periods, we only consider the member's first visit in each period. We include only physicians who conducted at least one in-person and one remote visit during the post-lockdown period. Our resulting samples have 14,800 observations for UTI, 10,100 observations for AMI, and 8,500 observations for fracture. 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 discussed in detail in the next section.

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

Condition-Specific Variables

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

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

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

Diagnosis Rates. We observe the rates of diagnosis of each of the target conditions, based on ICD9 codes recorded in visit summaries. Target diagnosis codes for each sample are listed in Panel A of Appendix Table A.5, Appendix

Table A.6, and Appendix Table A.7. We separately measure diagnosis rates during index visits and during the entire episode. We consider a diagnosis to have occurred during a visit if at least one target ICD9 was recorded. We consider a diagnosis to have occurred during an episode if it occurred during any encounter with a physician in a community setting (remotely or in-person) that took place over the 30-day period starting on the date of the index visit, including the index visit itself.

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

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

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

Appendix C: Sample and Variables Used for Analyzing Deferrability

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

Appendix D: Analysis Using an Alternative Post-Lockdown Period

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

Sample and Variable Definitions

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

Appendix Figure A.17 shows descriptive statistics on telemedicine use, COVID-19 cases, and primary care volume during the original study periods and leading up to our alternative post-lockdown period. Two facts emerge that motivate the focus on the alternative post-lockdown period. First, while there is a clear correlation between COVID-19 cases and telemedicine use throughout 2020–2021, telemedicine use also exhibits a ratchet effect: it remains at a much higher level than the pre-period baseline during both periods we observe during which Israel had nearly zero COVID-19 cases, including after the apparent end of the epidemic. In both our original and alternative post-lockdown periods, about 20% of new primary care episodes start remotely. Second, unlike the first post-lockdown period, which was preceded by a very sharp decrease in utilization of primary care (and healthcare services more generally) that was associated with the first COVID-19 lockdown, the rest of 2020 and the first half of 2021 saw a normalization of the pandemic and much higher rates of primary care utilization. Therefore, we argue that our alternative post period provides a useful context to study post-COVID-19 telemedicine use, and it is less susceptible to concerns regarding the impact of COVID-19 and the disruption to healthcare utilization brought by it.

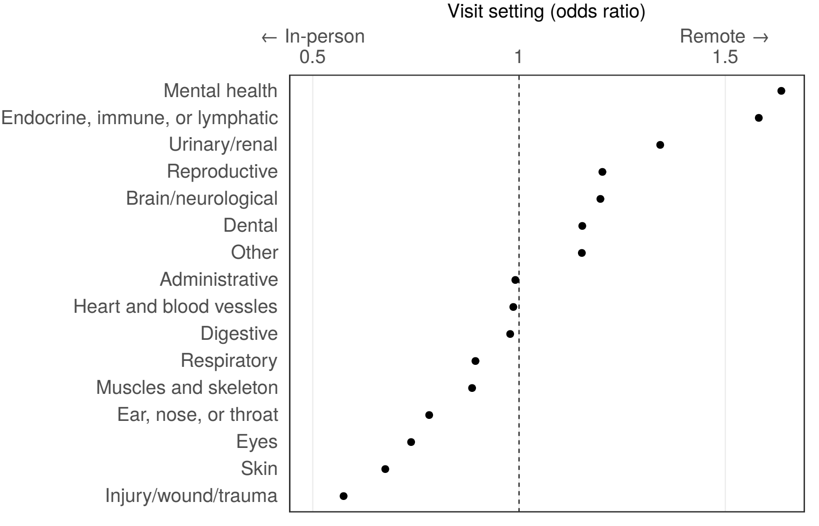
Using the alternative post-lockdown period, we consider the impact of increased access to telemedicine on the following outcomes: overall demand for primary care (defined as the probability of a non–follow-up primary care visit during the post-lockdown period), in-visit actions during the index primary care visit, and physician follow-ups in the 7-day period following an index primary care visit.

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

Results

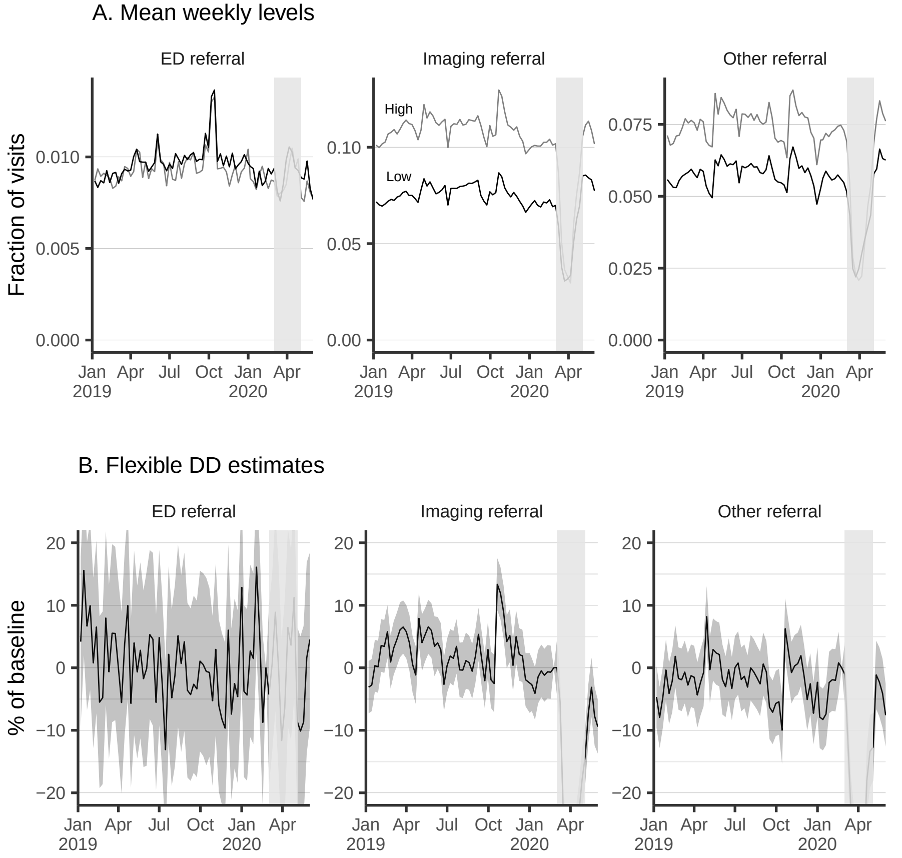
Table 5, Table 6, and Appendix Figure A.5 show estimates for the impact on different outcomes of increased access to telemedicine in the alternative post-lockdown period. Greater access to telemedicine is associated with a 3.5% increase in the share of members who have a primary care episode during the alternative post-lockdown period—nearly identical to the 3.5% increase estimated using the original post-lockdown period. Similar to the original post period, increased access to telemedicine is associated with a 4.4% lower rate of prescriptions during the index visit, and is not associated with any significant increase in referrals. The estimated impacts on 7-day physician visits (+2.4%), visits with the same physician (+2.6%), and in-person visits (−4.9%) maintain the same sign as in our main analysis, though the magnitude of theses effects is smaller. Overall, the stability of our results over different periods suggests that they are not driven by idiosyncratic shocks specific to either period.

FIGURE A.1. Remote medicine relative use, by diagnostic category.



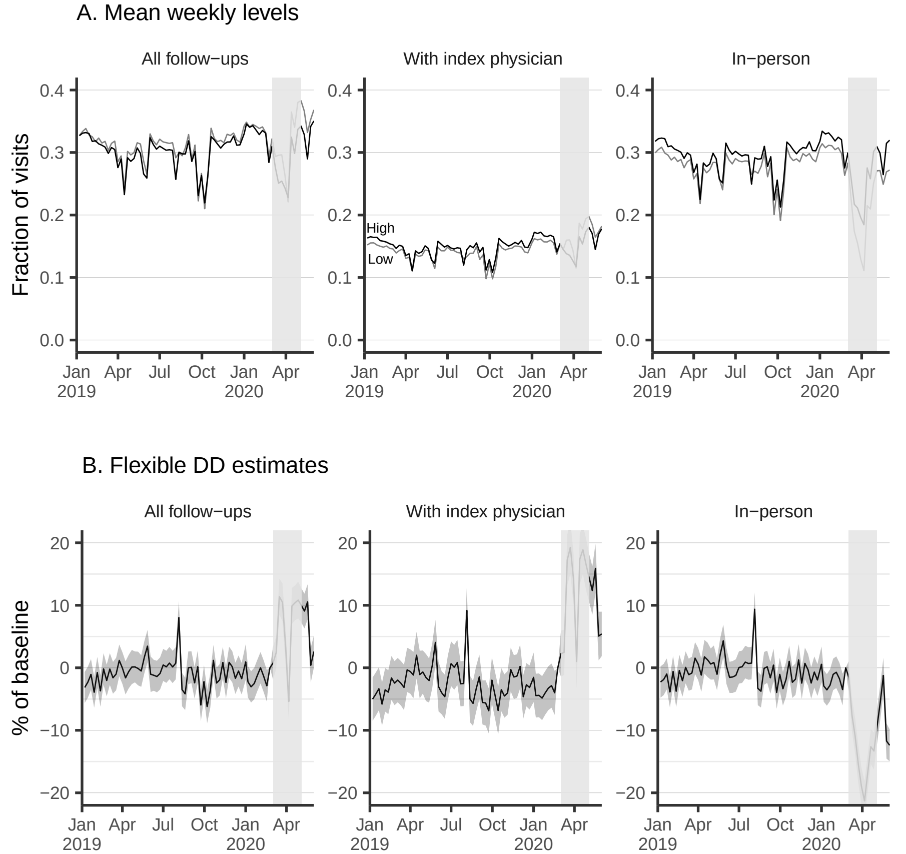
The figure shows the relative propensity of patients to use telemedicine (remote) versus in-person care for different categories of medical conditions. That is, using the post-lockdown sample of index (non–follow-up) primary care visits, the figure shows for each diagnostic category, the odds ratio (OR)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

FIGURE A.2. Flexibly estimated time trends in additional visit outcomes, by physician telemedicine use during the lockdown period.



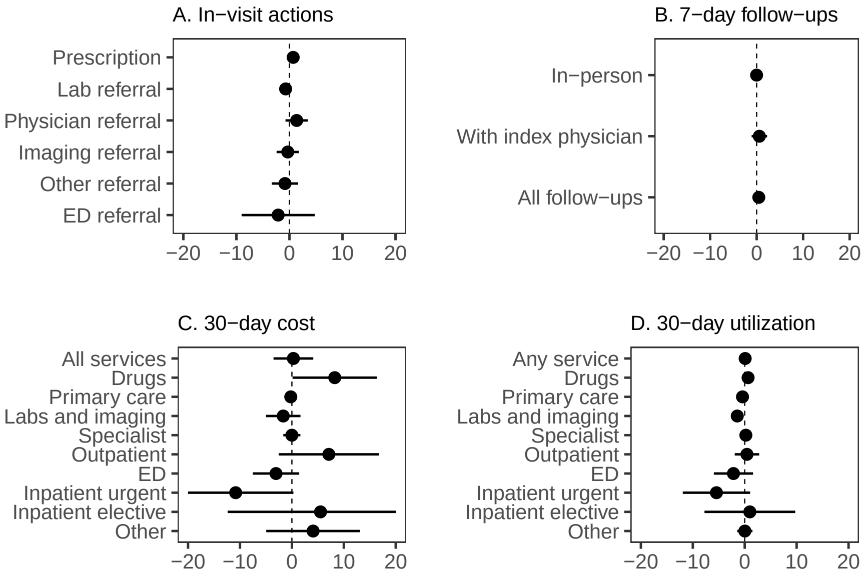
The figure shows, using the sample of all visits starting new primary care episodes, flexibly estimated time trends for all visit outcomes that were not included in Figure 4. Panel A shows raw (unadjusted) weekly means for visits of patients affiliated with high telemedicine adopters (High) and low telemedicine adopters (Low). Panel B shows flexible difference-in-differences estimates of the impact of high access to telemedicine from a version of equation (2) with the same fixed effects and controls but with fully flexible week 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.

Figure A.3. Flexibly estimated time trends in physician follow-ups, 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 7-day physician follow-up visits. Panel A shows raw (unadjusted) weekly means for visits of patients affiliated with high telemedicine adopters (High) and low telemedicine adopters (Low). Panel B shows flexible difference-in-differences estimates of the impact of high access to telemedicine from a version of equation (2) with the same fixed effects and controls but with fully flexible week indicators, and the same week indicators interacted with an indicator for High. The figure shows the estimates of the interacted week indicators (week $\times$ High) relative to the (omitted) last week of the pre-lockdown period. The 95% confidence interval is shown in dark gray. For comparability, estimates and their confidence intervals are expressed as a share (percent) of each mean outcome in the pre-lockdown period. The shaded light gray rectangles mark the lockdown period, which we only use for the measurement of telemedicine adoption but otherwise exclude from the analyses. Outcomes are not mutually exclusive. See Section 2.2 for detailed variable definitions.

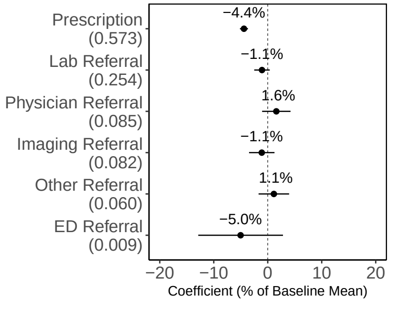
FIGURE A.4. Placebo analyses.



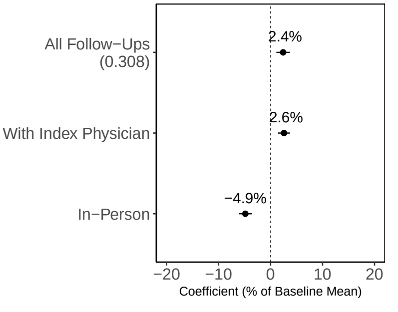
The figure shows placebo analyses. For each set of outcomes, we reproduce our main difference-in-differences estimates using equation (2), replacing the actual study sample with a "placebo" sample in which the pre period is January–February 2019 and the post period is January–February 2020. Because this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

FIGURE A.5. The impact of increased access to telemedicine on index visit in-visit actions and 7-day follow-ups, alternative post-lockdown period.

(A) In-visit actions

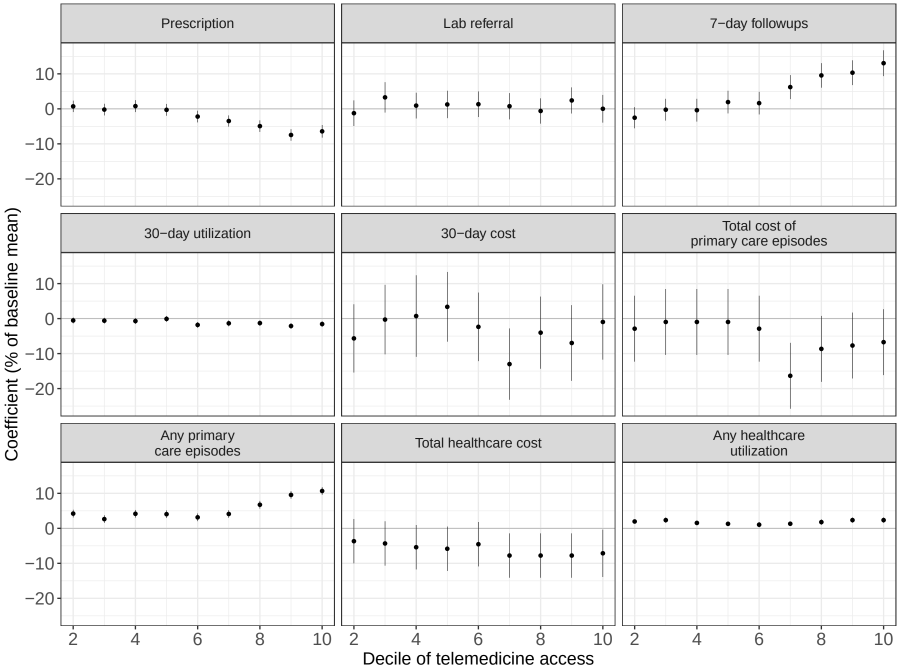


(B) 7-day physician follow-ups



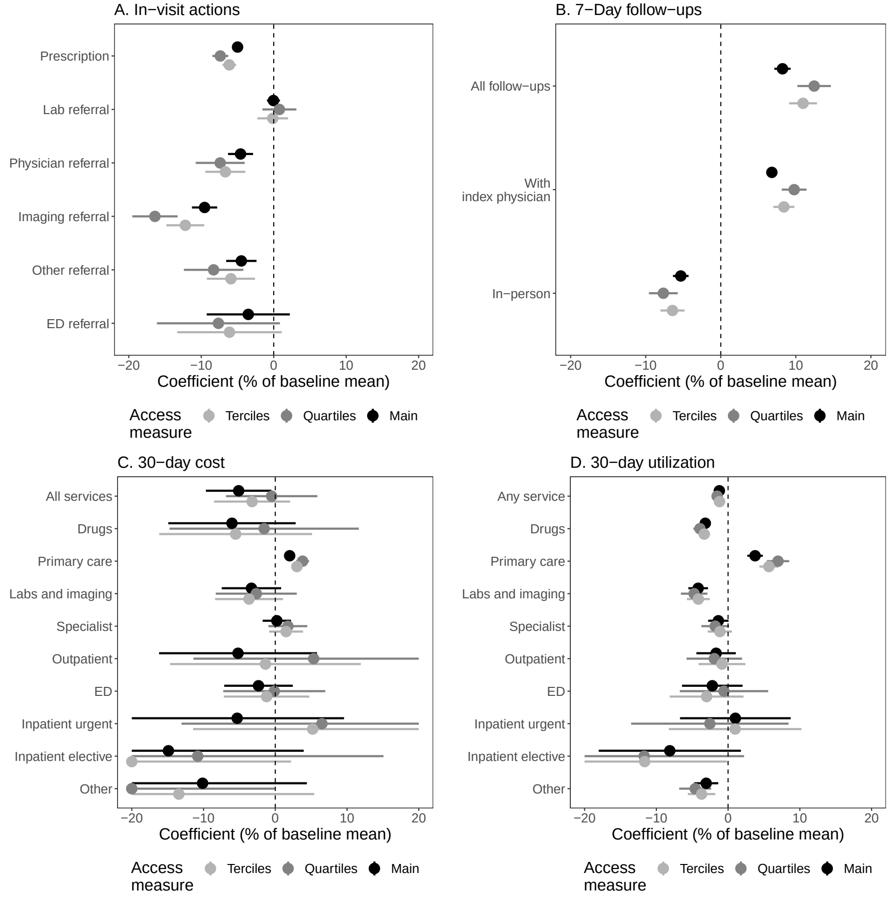
The figure shows the estimated impacts of increased access to telemedicine on visit outcomes using the alternative post-lockdown period of April–May 2021. Each row shows the difference-in-differences estimate for the impact of increased access to telemedicine (β from equation (2)) for a different outcome. 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). The sample includes all new primary care episodes in the pre-lockdown period of January 2019–February 2020 and the alternative post-lockdown period of April–May 2021. The outcomes shown are for the first visit of each episode. Outcomes are sorted by their pre-lockdown mean. Outcomes are not mutually exclusive. Appendix D discusses the sample details.

FIGURE A.6. Heterogeneity in results by deciles of access to telemedicine.



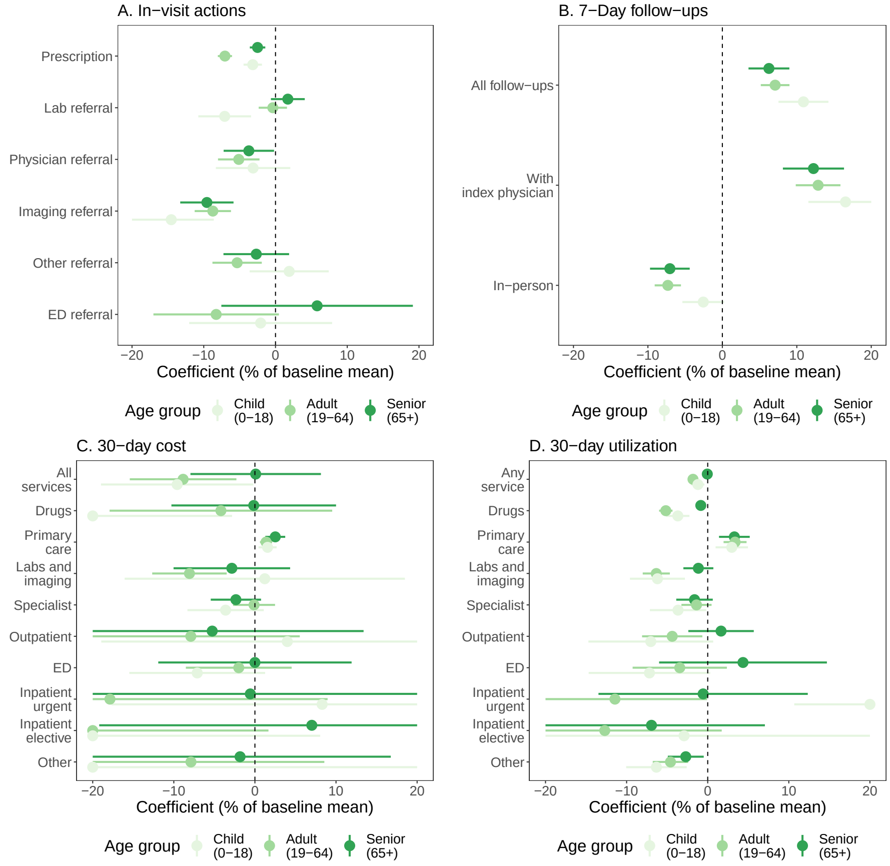
The figure shows estimates for the impact of increased access to telemedicine on different key outcomes by decile. These estimates were obtained using the same sample as the main study, by estimating a version of equation (2) where we interact $Post_t$ with each decile of α_j, with the lowest decile as the omitted category. Each plot shows the resulting estimates on these interaction terms for a different outcome. For comparability across outcomes and with our main results, all estimates are shown as a percentage of the baseline (pre-period) level of each outcome. error bars show the 95% confidence interval of each estimate.

FIGURE A.7. Robustness: the impact of increased access to telemedicine on index visit outcomes using alternative access measures.



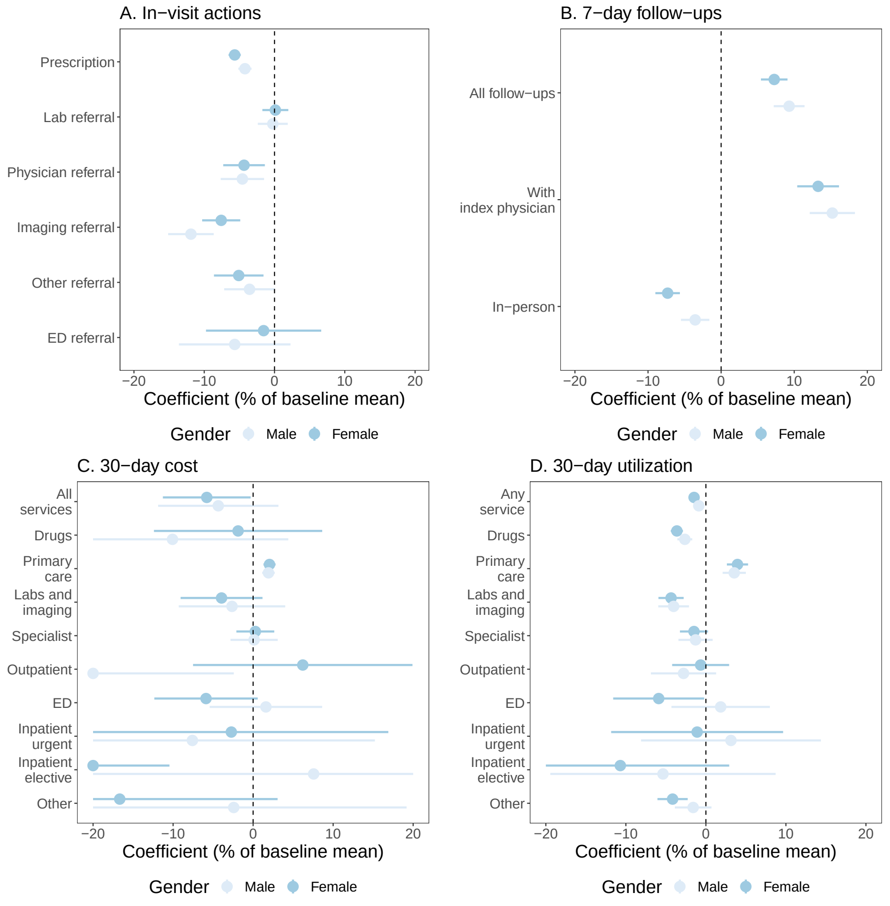
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, using alternative measures of telemedicine access that are based on defining high and low access based on the top and bottom terciles or quartiles of adopters; for ease of comparison, our main specification that is based on a definition of access that is based on above- and below-median adopters is also shown (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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.

Figure A.8. The impact of increased access to telemedicine on visit outcomes, follow-Ups, and 30-day cost and utilization, by patient age.



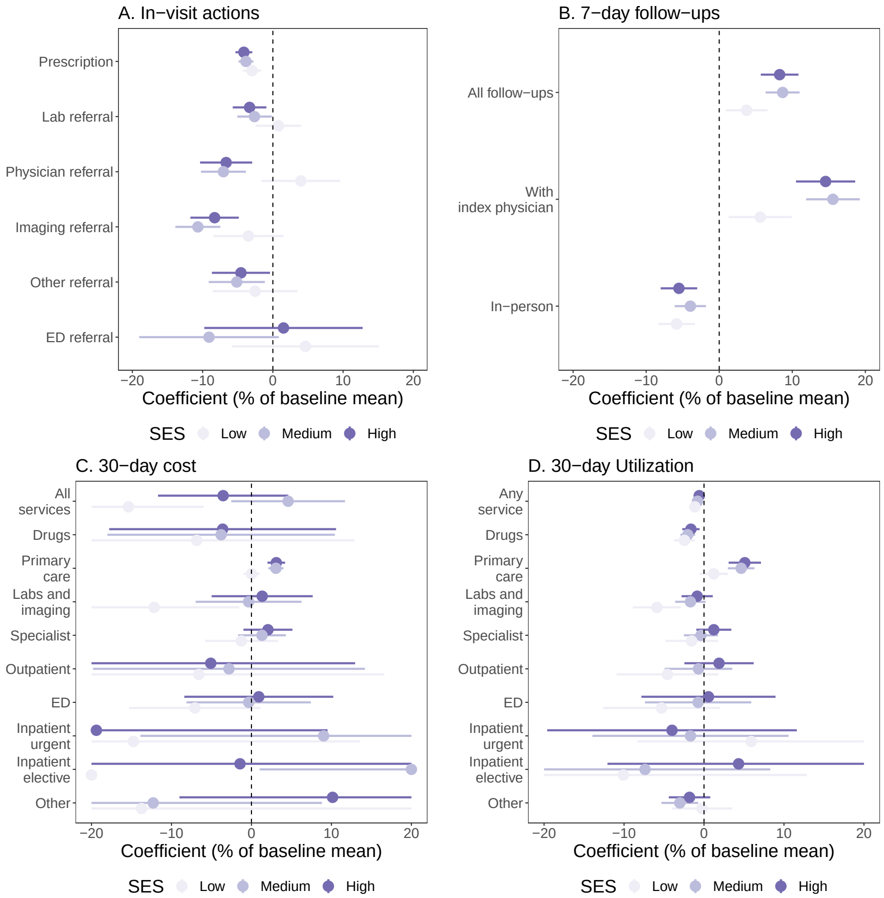
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different ages at the time of the first visit (see legend). The sample includes all new primary care episodes. Each row shows an estimate of β from equation (2) for a different outcome. 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.9. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by patient gender.



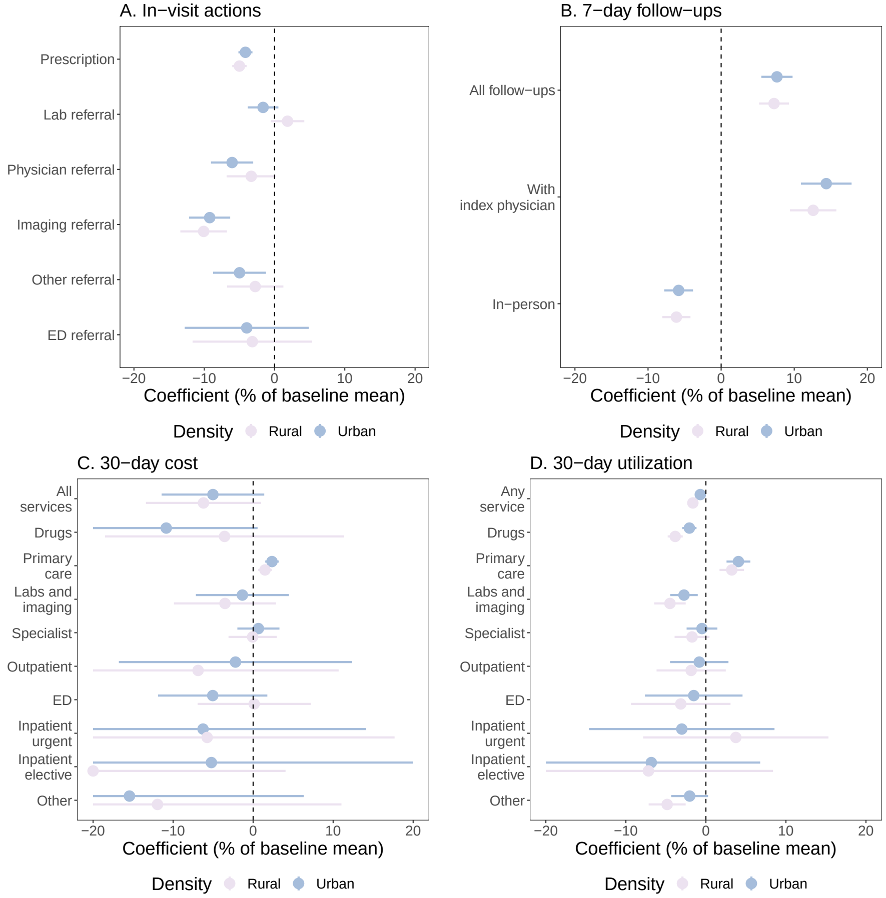
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different genders (see legend). The sample includes all new primary care episodes. Each row shows an estimate of β from equation (2) for a different outcome. This coefficient captures 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.10. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by socioeconomic status.



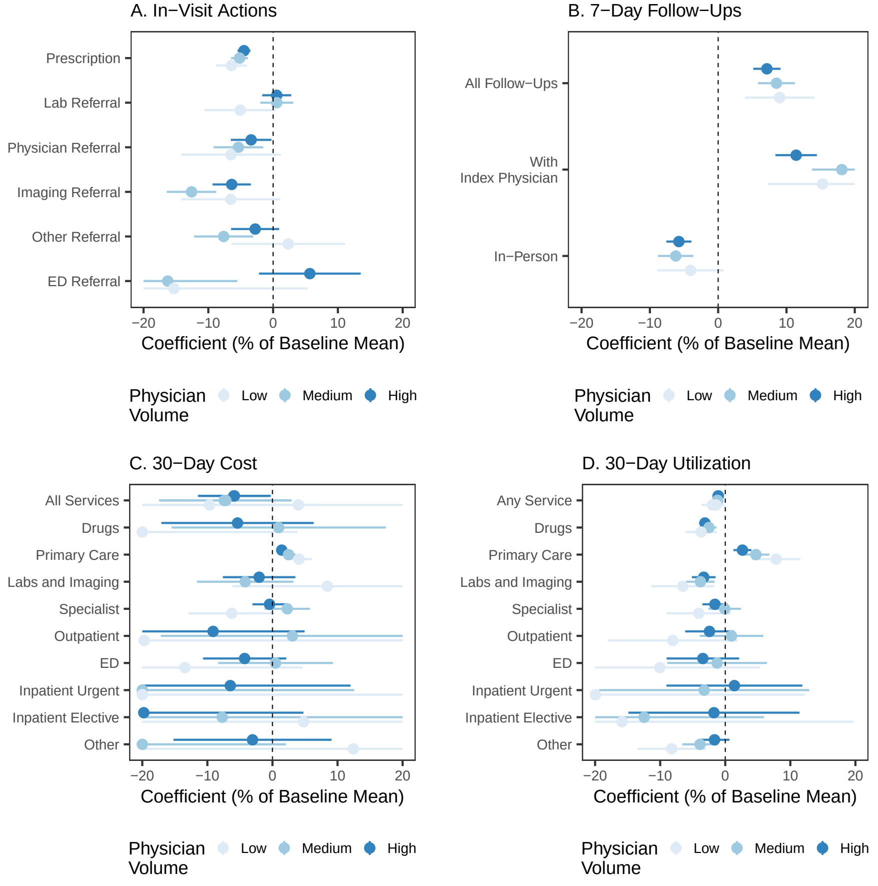
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients of different terciles of a socioeconomic status score defined based on the average income at the patient place of residence (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.11. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by urbanicity.



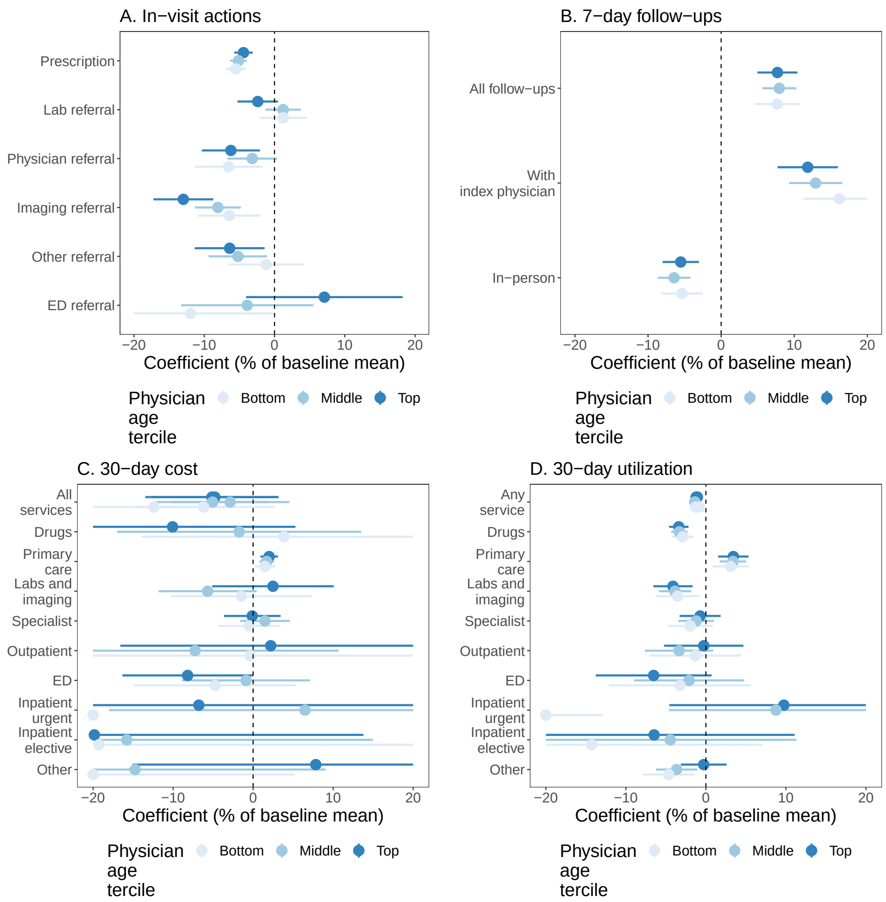
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, for patients residing in urban and rural places (see legend). The sample includes all new primary care episodes. Each row shows an estimate of β from equation (2) for a different outcome. This coefficient 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.12. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by physician pre-period volume.



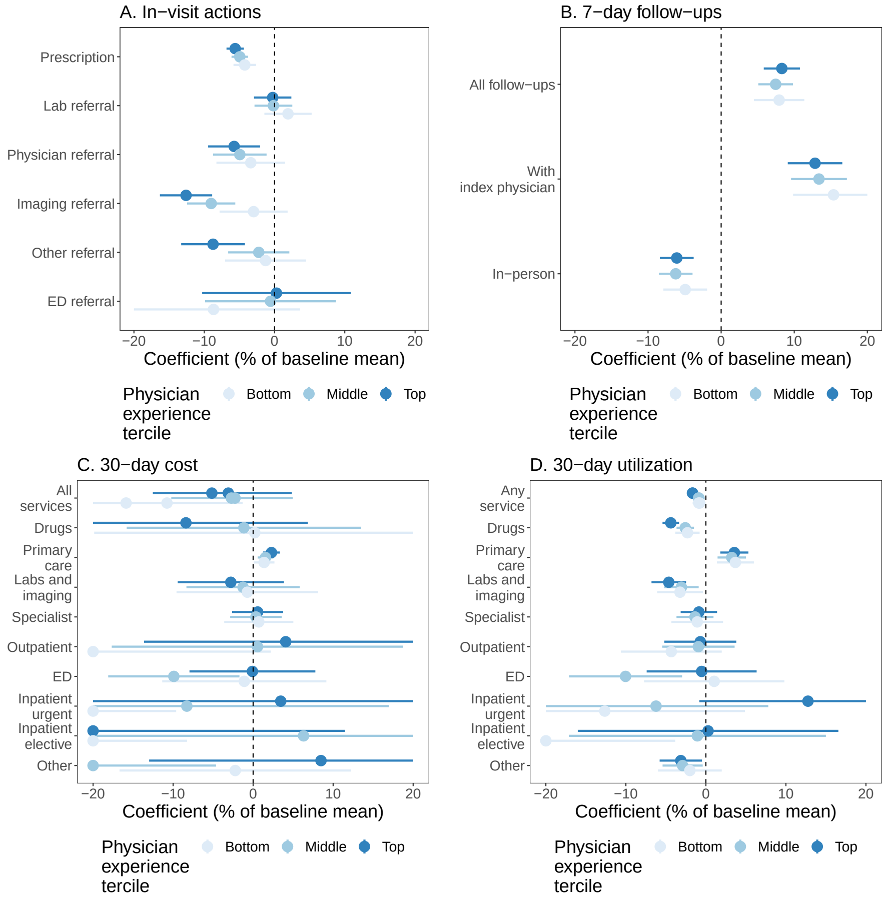
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by terciles of the weekly number of visits of the patient's main primary care physician in the pre-lockdown period (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.13. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by physician age.



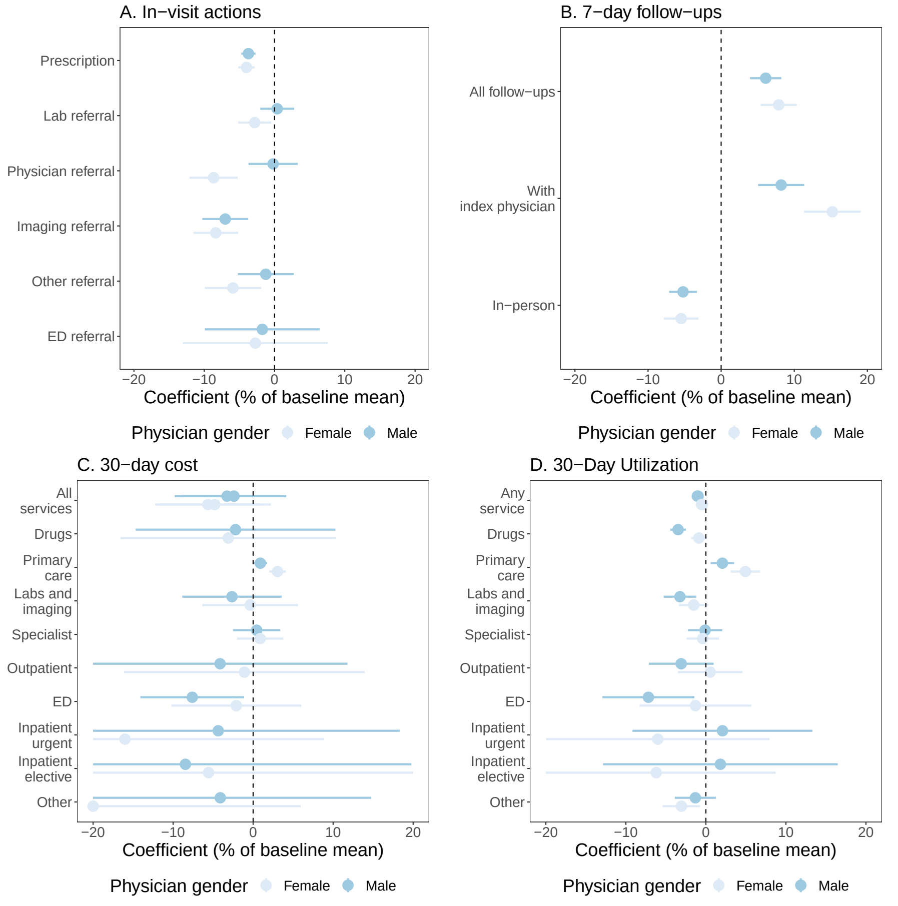
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by age group of the patient's main primary care physician in the pre-lockdown period (see legend). The sample includes all new primary care episodes. Each row shows an estimate of β from 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.14. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by physician experience.



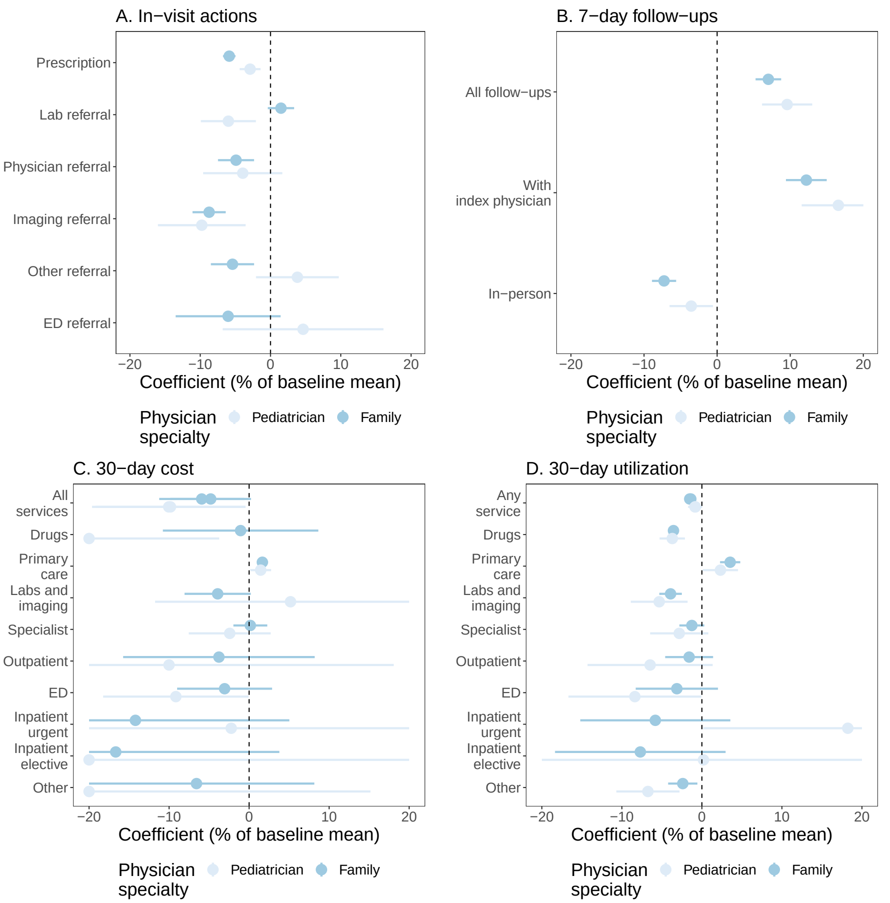
The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by terciles of the experience of the patient's main primary care physician in the pre-lockdown period (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.15. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by physician gender.



The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by the gender of the patient's main primary care physician in the pre-lockdown period (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.16. The impact of increased access to telemedicine on visit outcomes, follow-ups, and 30-day cost and utilization, by physician specialty.



The figure shows the estimated impacts of increased access to telemedicine on visit and episode outcomes, separately by the specialty of the patient's main primary care physician in the pre-lockdown period (see legend). The sample includes all new primary care episodes. Each row shows an estimate of 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 6.2 discusses in more detail the sample and variable definitions.

FIGURE A.17. Share of visits provided remotely, COVID-19 cases, and average primary care utilization 2020–2021.

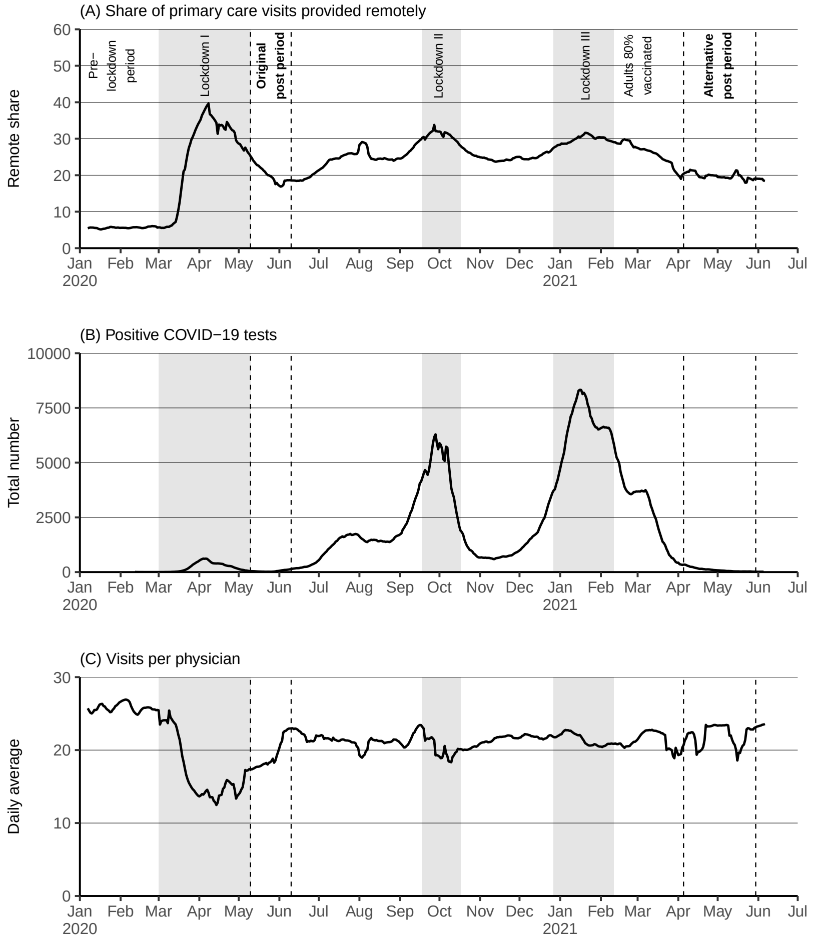


Figure shows different statistics for the period leading up to our alternative post-lockdown period. Gray-shaded areas refer to lockdown periods. The areas between the two vertical dashed lines refer to this study's original and alternative post-lockdown periods (original: May 11, 2020, to June 7, 2020;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

Table A.1. Telemedicine adoption by patient characteristics, different periods.

	Lockdown period (1)	Post-lockdown period (2)	Alternative post period (3)
A. Gender			
Female	29.7%	23.0%	22.8%
Male	25.2%	19.2%	18.8%
B. Age			
0–18	18.3%	17.2%	16.3%
19–64	25.4%	21.6%	22.4%
65+	38.2%	23.8%	22.5%
C. Socioeconomic status			
Low	24.0%	18.1%	18.8%
Medium	35.8%	28.1%	26.2%
High	27.1%	20.6%	18.5%
D. Number of chronic conditions			
0	20.4%	18.7%	18.6%
1–2	24.1%	20.8%	21.8%
3+	32.5%	22.7%	22.8%
E. ACG tercile			
Low	22.3%	19.1%	18.6%
Medium	29.3%	21.7%	21.8%
High	31.1%	23.7%	22.9%
F. Urbanicity			
Rural	23.7%	18.2%	18.4%
Urban	32.5%	25.1%	24.2%

The table shows the rates of telemedicine use in different periods and for different subgroups of patients (row panels) and periods (columns). Each cell shows, for the respective group and period, the average share of all primary care physician visits that occured remotely. See Section 2.2 and Appendix A for detailed variable and period definitions.

TABLE A.2. Telemedicine adoption by physician characteristics.

Adoption rate	Lockdown period		Post-lockdown period		Alternative post period	
	Raw	Residualized	Raw	Residualized	Raw	Residualized
	(1)	(2)	(3)	(4)	(5)	(6)
A. All physicians						
	27.7%	27.7%	21.3%	21.3%	21.1%	21.1%
B. Physician gender						
Female	38.0%	36.4%	29.3%	28.7%	28.8%	28.3%
Male	20.5%	21.6%	15.4%	15.8%	15.9%	16.1%
C. Specialty						
Family	29.4%	28.1%	22.2%	21.6%	22.1%	21.2%
Pediatrician	19.5%	26.1%	17.5%	20.3%	17.3%	20.7%
D. Age tercile						
Bottom	30.7%	31.1%	23.3%	23.5%	21.9%	21.9%
Middle	28.8%	28.3%	22.3%	22.0%	22.3%	22.1%
Top	24.1%	24.3%	18.7%	18.8%	19.0%	19.2%
E. Experience tercile						
Bottom	26.3%	27.4%	20.4%	20.9%	20.0%	20.3%
Middle	28.9%	28.9%	22.3%	22.2%	22.0%	21.9%
Top	27.8%	26.9%	21.2%	21.0%	21.1%	20.9%
F. Level of activity in pre-period						
Bottom	31.3%	30.7%	23.1%	23.0%	21.6%	22.0%
Middle	35.1%	33.6%	27.3%	26.9%	25.8%	25.5%
Top	23.9%	24.7%	18.4%	18.6%	19.0%	19.0%
G. Propensity for referrals in pre-period						
Bottom	15.9%	18.8%	12.4%	13.4%	13.7%	14.5%
Middle	25.9%	26.2%	19.5%	19.6%	20.1%	20.2%
Top	40.7%	37.8%	31.3%	30.2%	29.7%	28.7%
H. Propensity for prescriptions in pre-period						
Bottom	27.4%	27.7%	21.5%	21.7%	20.5%	21.1%
Middle	28.7%	28.0%	22.1%	21.8%	21.8%	21.5%
Top	27.0%	27.6%	20.6%	20.8%	20.9%	20.7%

The table shows the rates of physician telemedicine adoption in different periods (column panels) for different subgroups of physicians (row panels). Odd-numbered columns show the average unadjusted share of each physician's visits that were conducted remotely for different periods. Even-numbered columns show rates residualized, obtained by averaging the residuals obtained by estimating a version of equation (1) with no fixed-effects, using data on all cases in each period, and averaging the residuals within each physician group. See Appendix A for detailed variable and period definitions.

Table A.3. Within-physician correlation in telemedicine adoption across patient types.

		Baseline	ACG		Age		Gender	
			High	Low	Old	Young	Female	Male
	Baseline	–	0.99	0.98	0.97	0.97	0.99	0.98
ACG:	High	0.99	–	0.96	0.97	0.95	0.98	0.97
	Low	0.98	0.96	–	0.94	0.97	0.97	0.98
Age:	Old	0.97	0.97	0.94	–	0.92	0.96	0.96
	Young	0.97	0.95	0.97	0.92	–	0.96	0.96
Gender:	Female	0.99	0.98	0.97	0.96	0.96	–	0.96
	Male	0.98	0.97	0.98	0.96	0.96	0.96	–

The table shows the results of auxiliary analyses in which we estimate α_j, the tendency of physicians to adopt telemedicine during the lockdown period (using equation (1)), separately for patient subgroups defined by the patient's ACG, age, and gender. Each estimation sample—ACG (above and below median), age (above and below median), and gender—includes only physicians with at least ten patients of each type (High/Low, Old/Young, Female/Male). We then associate each physician with a vector $\alpha = (\alpha_j^{\text{Baseline}}, \alpha_j^{\text{High ACG}}, \alpha_j^{\text{Low ACG}}, \alpha_j^{\text{Old}}, \alpha_j^{\text{Young}}, \alpha_j^{\text{Female}}, \alpha_j^{\text{Male}})$, where Baseline refers to the original α_j using the full sample. The table shows pairwise correlations between all pairs of α_j.

TABLE A.4. Physician and case characteristics, by physician telemedicine adoption status.

	High (1)	**Low** (2)
A. Physician characteristics		
Age	51.6	54.5
Female	0.589	0.312
Years in practice	15.5	16.4
Pediatrician	0.201	0.306
High volume	0.355	0.450
High prescriber	0.330	0.337
High referrer	0.458	0.210
Share remote	0.319	0.061
Weekly visits	89.9	96.7
Number of physicians	2,146	2,147
B. Case characteristics (affiliated patients)		
Age	40.7	34.7
Female	0.559	0.539
High Socioeconomic Status	0.373	0.223
ACG	1.16	0.97
Number of chronic conditions	2.97	2.36
Share remote	0.303	0.083
Number of visits	251,434	304,203

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

Table A.5. Target conditions and differential diagnoses for the UTI sample.

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

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

Table A.6. Target conditions and differential diagnoses for the AMI sample.

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

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

Table A.7. Target conditions and differential diagnoses for the fracture sample.

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

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

Table A.8. Patient characteristics, specific conditions.

	UTI (1)	AMI (2)	Fracture (3)
A. All Conditions			
Age	43.6	53.3	35.2
Female	0.669	0.506	0.414
ACG	1.46	1.84	
Number of chronic conditions	0.155	0.201	0.122
B. UTI			
UTI in last year	0.204		
Number of UTI months in last five years	2.08		
C. AMI			
Smoker		0.183	
Systolic BP		123.6	
Total cholesterol		176.6	
HDL cholesterol		48.4	
History of anti-hypertensives		0.433	
History of diabetes		0.293	
D. Fracture			
History of osteoporosis			0.066
Head injury			0.077
Torso injury			0.148
Arm injury			0.234
Leg injury			0.183
Number of physicians	3,309	2,570	2,801
Number of visits	14,877	10,105	8,550

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

Table A.9. The impact of access to telemedicine on visit and episode outcomes.

	Pre-lockdown mean (1)	Estimated impact (2)	(S.E.) (3)	Percentage impact (4)
A. In-visit actions				
Prescription	0.573	-0.0286	(0.0013)	-5.0%
Lab referral	0.254	-0.0001	(0.0012)	0.0%
Physician referral	0.085	-0.0039	(0.0007)	-4.6%
Imaging referral	0.082	-0.0079	(0.0007)	-9.5%
Other referral	0.060	-0.0027	(0.0006)	-4.5%
ED referral	0.009	-0.0003	(0.0003)	-3.5%
B. Number of 7-day physician follow-ups				
All follow-ups	0.308	0.0253	(0.0017)	8.2%
With index physician	0.147	0.0210	(0.0011)	14.3%
Not with index physician	0.160	0.0044	(0.0012)	2.7%
Remote	0.018	0.0417	(0.0004)	228.0%
In-person	0.289	-0.0164	(0.0016)	-5.7%
C. 30-day utilization				
All services	0.855	-0.0104	(0.0015)	-1.2%
Drugs	0.673	-0.0214	(0.0023)	-3.2%
Primary care	0.422	0.0159	(0.0023)	3.8%
Labs and imaging	0.342	-0.0143	(0.0024)	-4.2%
Specialist	0.248	-0.0034	(0.0018)	-1.4%
Outpatient	0.080	-0.0013	(0.0011)	-1.7%
ED	0.031	-0.0007	(0.0007)	-2.2%
Inpatient urgent	0.009	0.0001	(0.0003)	1.0%
Inpatient elective	0.006	-0.0005	(0.0003)	-8.1%
Other	0.268	-0.0082	(0.0023)	-3.1%
D. 30-day cost (NIS)				
All services	565	-28.84	(13.1588)	-5.1%
Drugs	118	-7.13	(5.3432)	-6.0%
Primary care	86	1.73	(0.2720)	2.0%
Labs and imaging	58	-1.93	(1.2268)	-3.3%
Specialist	30	0.06	(0.2982)	0.2%
Outpatient	44	-2.26	(2.4474)	-5.2%
ED	24	-0.56	(0.5830)	-2.3%
Inpatient urgent	112	-5.95	(8.5119)	-5.3%
Inpatient elective	70	-10.38	(6.7054)	-14.9%
Other	24	-2.42	(1.7725)	-10.1%

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