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Adoption and utilization of device-assisted telemedicine[☆]

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ABSTRACT

We estimate the effect of adopting a digital device for performing medical exams at home during telehealth visits. We match visits of adopters and non-adopters who used the same virtual care clinic but without the device and compare healthcare utilization after the matched visits. We find that device adoption, partially offset by decreased use of other primary care modalities, results in a 12% higher utilization rate of primary care and increased use of antibiotics. But – particularly among adults – adoption lowers the use of urgent care, the emergency room, and hospital care, resulting in no increase in total cost.

1. Introduction

Telemedicine has been growing rapidly over the past few years and is estimated to continue to grow even further (Hollander and Carr, 2020; Patel et al., 2021; Bestsennyy et al., 2022; Friedman et al., 2022; Zeltzer et al., Forthcoming). A key challenge for shifting care remotely is the need for physical examination, which is required for diagnosing and managing many medical conditions (Hyman, 2020). This has spurred innovation in digital health technologies – including wearables, personal devices, and sensors – that aim to bridge this gap.[1] Major insurers, including Medicare, already cover their use (CMS, 2021). Yet, as the adoption of such technologies is very recent, little evidence exists about their actual impact. The increased convenience for patients and the hope for improved care quality and availability are accompanied by concerns regarding overuse and increased spending (Ellegård et al., 2021; Mecklai et al., 2021; Perakslis and Ginsburg, 2021).

In this paper, we study the adoption of a digital device for performing medical exams at home as part of telemedicine visits, with the aim of facilitating medical diagnosis and expanding the range of conditions that can be treated remotely. Patients who

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[1] According to McKinsey, venture funding for digital health companies hit a record of $29.1 billion in 2021, up from $8.2 billion in 2019 (Bestsennyy et al., 2022).

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purchase the device can measure temperature and record high-definition video and sound using special adapters that allow for the examination of the mouth, ears, lungs, heart, and skin. Patients can then transmit the information to physicians in a virtual primary care clinic, either before or during the (virtual) visit.

We use comprehensive claims data from the largest Israeli HMO from 2018–2022, covering the entire period of device adoption. Our study sample consists of over 100,000 device-assisted visits by over 28,000 device adopters. Adopters tend to have higher-than-average socioeconomic status, and more than half are parents of young children who use it for pediatric visits. These visits mainly involve diagnoses for respiratory, ear, and eye conditions, for which physicians mainly prescribe medications. We combine data on device use with data on patient care across all settings, both before and after device adoption, to estimate its impacts on care utilization and cost. A key strength of these data is that they allow us to estimate the device's impact on the utilization and cost of all other services beyond the immediate setting in which it is used.

The main identification challenge is that voluntary device adoption may be associated with persistent and transitory shocks to underlying patient health, which may confound the association between device adoption and outcomes. Concerns regarding such selective adoption are somewhat reduced because the device is mainly used for treating minor and very common acute conditions, which are relevant to the entire population. However, to mitigate any remaining concerns regarding endogenous adoption, we match device adopters with non-adopters who visited the same virtual primary care clinic for a regular video visit without the aid of the device, and who also match on other individual characteristics and detailed six-month healthcare utilization history. We then compare the utilization and cost of primary care and other healthcare services used by adopters and non-adopters throughout the first full year that follows the initial device-assisted (and matched non-assisted) visit.

Our results indicate that initial adoption is followed by an incremental increase in telehealth visits assisted by the device. This increase in device-assisted visits is partly – but not entirely – offset by a reduction in visits in other settings. Overall, the device adoption leads to a net 12% increase in primary care visits—approximately one additional primary care visit per member per year. Concurrently, prescription drug use—particularly antibiotics—increases. Conversely, utilization of more intensive care, including urgent care, the ER, and hospital admissions, significantly decreases. Overall, the results suggest that device adoption increases the overall utilization of primary care, expands the share of such care done remotely, and decreases care utilization in more intensive settings. Consequently, despite its incremental impact on primary care use, device adoption does not increase healthcare costs. These effects differ substantially for pediatric and adult use, with the reduction in urgent care, ER, and hospital use driven mainly by the latter.

To examine how the effects on different outcomes are related, we measure the impact of device adoption separately for different groups of patients. We then correlate the effect of adoption on different healthcare services. The effects of adoption on primary care are positively correlated with the effects on prescription drugs, testing, specialist use, urgent care, and (more noisily) hospital use. It is negatively correlated with the effects on ER. These correlations may suggest that device-assisted visits can effectively triage cases, particularly for adult patients, directing them toward the more suitable (and on average cheaper) usage of urgent care centers instead of the ER.

One might be concerned that COVID-19, which spurred the adoption of telemedicine modalities, confounds our findings. However, only about 1% of device-assisted and matched visits in our (post-March 2020) sample involved a COVID-19 diagnosis because the HMO operated dedicated channels for inquiries related to COVID-19. We also include patient and calendar-week fixed-effects to account for distinctive preferences and constraints related to the COVID-19 pandemic. Finally, omitting periods of COVID-19 lockdowns from the sample does not change the results. It thus seems unlikely that the results are driven by COVID-19.

Taken together, our results demonstrate that the increased convenience and access associated with shifting visits from the clinic to the home may lead to increased primary care utilization. At the same time, the results suggest that a reduction in more costly care may offset this increase in primary care utilization. These effects exhibit marked heterogeneity by age, which suggests that—as telemedicine technologies continue to grow—the appropriate targeting of telehealth devices could be an important policy focus.

This work contributes to the fast-growing literature that considers the impacts of telemedicine, especially in the new era following its widespread adoption (Dahlstrand, 2021; Goetz, 2021; McCullough et al., 2021; Rabideau and Eisenberg, 2021; Zeltzer et al., Forthcoming). The rise in telemedicine has accelerated the development and adoption of innovation aimed at the collection of patient health data from electronic devices outside of traditional settings (Marra et al., 2020). Such innovation involves a broad range of devices: from wearable activity trackers used by healthy patients, through digital blood pressure cuffs or glucometers that transmit information to physicians for remote monitoring of chronic patients, to remote examination devices that allow patients to perform medical exams at home for the diagnosis of new conditions.[2] This paper provides novel evidence on the impacts of device-assisted telemedicine on the cost and use of care. Our current focus is on a device that facilitates remote diagnosis, in contrast to devices used for remote monitoring of patients with existing conditions (Mecklai et al., 2021).

The rest of the paper proceeds as follows. Section 2 discusses the clinical context. Section 3 discusses the data and empirical specifications and provides descriptive evidence on device use. Section 4 presents the estimates for the impact of device adoption on care utilization and cost. Section 5 concludes.

[2] These new services are now covered by major payors. Since 2018, the U.S. Centers for Medicare and Medicaid Services has covered the collection, transmission, evaluation, and communication of patient health data from electronic devices. Initially only covering care for established chronic patients, in 2021 and again in 2022, coverage has been expanded and now includes device use for new patients and for acute conditions (See https://www.ama-assn.org/system/files/2018-12/playbook-resources-step-5-coding-payment-REV1.pdf, accessed April 2023). Germany's 2019 Digital Healthcare Act also expanded insurance coverage to include digital health applications (Gerke et al., 2020; Stern et al., 2020).

2. Empirical setting

The study population includes members of Clalit Health Services (Clalit, in short), the largest of four HMOs in Israel that provide tax-funded universal coverage. The device we study (branded as TytoCare) allows patients to conduct medical examinations at home. It is designed to complement telehealth visits and extend the range of medical conditions that can be diagnosed and treated remotely. The device includes a high-resolution camera, microphone, and a thermometer. It can be attached to a series of adapters: an otoscope for examining the ear, a stethoscope for listening to the heart and lungs, and a tongue depressor to look at the throat. The camera can also take photos of the skin, mouth, and ears. Appendix Figure A1 shows a picture of the patient kit. The patients perform the exams at home and transmit the readings to the virtual clinic, guided by the app interface, through a mobile app before the visit. During the virtual video visit with the patient, the physician can review the recording and guide the patient to perform additional exams if needed.

Since 2015, Clalit has been operating a virtual primary care clinic ("Clalit Online"), where patients can initiate a video consult with a physician through a mobile app. The service is free for patients and does not require advanced scheduling. Initially, it was open from 8pm to midnight on weekdays and from 1pm to midnight on weekends; in the wake of the COVID-19 pandemic, service became available over extended hours, first from 4pm and later from 8am (rather than 8pm) through midnight. Clinicians have access to patients' electronic medical records, can electronically prescribe medications, refer patients to lab and imaging tests, and refer patients to follow-up care with their primary care physician, specialists, or the emergency room (ER).

In 2019, Clalit began offering device-assisted telehealth visits in its virtual primary care clinic to Clalit members who purchased the device. The device was advertised in national and local media, online, in HMO clinics, and through the HMO web portal and app. Ads predominantly targeted parents with young children and highlighted the potential substitution for in-person care in other settings, the convenience of use, and the fact that the service is free after the initial purchase. Members could purchase the device over the phone (via the HMO call center), online, or in select pharmacies. For most of the study period, the device was offered to Clalit members for a discounted price of 179 NIS (approximately 50 US dollars).[3] Patients opt into using the device, and the decision to adopt the device and use it was likely patient-driven, based on their exposure to advertisements and the perceived benefits of having the device for at-home medical exams. Upon receipt of the device, it is paired and activated through the HMO mobile app. Appendix A provides examples of device advertisements and more details on the device acquisition, activation, and use.

3. Data and empirical approach

3.1. Data

We use data from Clalit on the universe of patient care utilization and costs over the study period, which covers the entire period of device introduction. 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. Because the annual churn rate is extremely low (around 1%), the data cover a large and stable population.

Sample and matching. We focus our analysis on Clalit members of all ages who used the device at least once between December 2019 and October 2021. We refer to these members as *adopters*, and define the adoption time as the first device-assisted visit. Appendix Figure A2 shows device adoption and use over time. During our study period, 31,074 members adopted and used the device in 104,532 device-assisted visits. We restrict attention to 28,213 users who were continuously covered for at least six months before and one year after the first device use and for whom we observe all demographic characteristics.[4] This is our treatment sample.

As discussed below, our empirical approach involves matching adopters with similar members who visited the same virtual clinic but never used the device during the study period. We refer to the latter as *non-adopters*. To construct this matched sample, we matched each adopter's first-ever device-assisted video visit with one of the 982,939 (non-assisted) video visits by non-adopters at the same virtual clinic. We jointly refer to the matched pair of visits (i.e., the first-ever device visit for adopters and the video visit for non-adopters) as the *index visit*, the timing of which is normalized to time 0.

Outcome variables. We consider the effect of device adoption on three sets of outcomes: primary care visits, utilization of healthcare services, and healthcare cost. All outcomes are measured weekly for 26 weeks before and 51 weeks after the index visit.

The first set of outcomes includes the number of primary care visits. We group visits into four types: visits with any primary care physician in the clinic or over the phone (labeled In-Person and Phone, respectively) and visits to Clalit's virtual primary care clinic using video chat only or video chat and device-assisted exams (labeled Video and Video+Device, respectively).

The two other sets of outcomes are the utilization and cost of care by service type. We measure utilization for each sampled member, week, and type of service based on the number of distinct days with events billed for the service. We also check the robustness of our results to this measure by using an alternative measure: as an indicator variable, equal to 1 if the member used the specific service during the week and 0 otherwise. We group services into the following categories: primary care; lab and imaging tests; prescription drugs; antibiotics—a subset of prescription drugs that is of specific concern; specialists; urgent care centers;

[3] The device list price is 450 NIS (approximately 125 US dollars).

[4] This sample restriction primarily excludes children younger than six months.

Table 1
Patient characteristics, main study sample.

	Adopters (1)	Non-Adopters (2)	Standardized Difference (3)
Age	17.25	17.24	<0.001
Female	0.544	0.544	<0.001
High SES	0.624	0.624	<0.001
Num of CC	1.06	1.07	0.006
ACG	0.76	0.71	–0.054
PCP Visits in Prior Year	8.06	8.44	0.047
Total Cost in Prior Year (NIS)	3,357	3,647	0.038
Number of Members[a]	28,213	394,974	

Table shows descriptive statistics for the main study sample. Adopters are members with at least one device-assisted telehealth visit (Video + Device) during the study period. Non-Adopters are matched members who never used the device during the study period and had a regular telehealth (Video) visit. Standardized Difference is Cohen's D, i.e., the difference in sample means divided by their pooled standard deviation $((m_{\mathrm{A}}-m_{\mathrm{NA}})/\sqrt{(s_{\mathrm{A}}^2+s_{\mathrm{NA}}^2)/2}$, where m, s are the sample means and standard deviations for Adopetrs (A) and Non Adopters (NA)). High SES is an indicator for the patient residing in an above-median socioeconomic status geographic cluster. Num of CC is the number of chronic conditions recorded for the patient in the HMO registry. ACG is the Johns Hopkins Adjusted Clinical Group risk classifier score (representing the expected cost relative to the population average, normalized to one). Total Cost in Prior Year includes the cost of all healthcare services 12 months before the index visit.
[a]The non-adopter sample includes one matched non-adopters for each of the 28,213 device adopters and each of the 14 different outcomes (excluding eight non-matches out of a total of $14 \cdot 28,213 = 394,982$ potential matches). Section 3 describes the sample, variables, and matching procedure in detail.

emergency room (ER); inpatient admissions; and all other services. We aggregate utilization across all services by either summing up event counts or, for the alternative measure, by recording an indicator equal to 1 if the member used any service during the week and 0 otherwise. We measure cost as the sum of the cost of services of each type that were used during each week and the total cost of all services. Costs are denominated in current New Israeli Shekels (NIS).[5,6] Appendix B provides detailed definitions of all variables.

3.2. Descriptive patterns

Device adopters are younger and of higher socioeconomic status than the average Clalit member. Appendix Table A1 compares the demographic characteristics of adopters and a random (non-matched) sample of the same size out of all non-adopter Clalit members. Most device adopters are young children who use it for pediatric visits. The median adopter's age is six years, compared with 32 years for the median Clalit member (which is close to the median age in Israel). About a third of adopters are adults, most of whom are parents (namely, have child dependents). Only 6% are older than 45 years, compared with 35% of non-adopter Clalit members. Adopters tend to live in locations associated with higher socioeconomic status than those of non-adopters. These differences motivate our use of matching.

Table 1 describes the characteristics of our main sample of 28,213 adopters and the matched non-adopters. The match quality appears high: there are only minor differences between adopters and non-adopters in ACG score, number of primary care visits and total cost in the year before the index visit, and number of chronic conditions, even though we did not directly match on these characteristics (all differences are smaller than 0.1 pooled standard deviations). Appendix Table A2 summarizes the means of all outcomes over the study period.

To gain insights into when and how the device is being used, we compare primary care episodes of adopters and non-adopters that started after adopters already had the device. We define primary care episodes as those starting with an in-person, phone, video, or device-assisted video visit, following at least 30 (consecutive) days with no encounters. Appendix Figure A3 describes the distribution of the time of day and the day of the week of the device versus in-person visits for adopters after they have adopted the device. Approximately 60% of device-assisted visits occur outside of regular hours (i.e., at night or during the weekend), compared with only 16% of in-person visits. Appendix Figure A4 compares the distribution of the main visit diagnosis between visits by adopters (with and without the device) and non-adopters. Adopters' other visits have a similar distribution of diagnoses as visits by non-adopters. Naturally, device visits mainly involve conditions that the device helps diagnose: respiratory, mouth, ear, and eye conditions. Less than 1% percent of device-assisted visits involve a COVID-19 diagnosis (or a note for suspected COVID-19).[7]

[5] During the study period, the exchange rate was approximately 3.5 NIS per US dollar.

[6] Because primary care physicians are salaried and are not paid fee-for-service, we impute a price for these encounters. We use the same price for all primary care visits, regardless of setting (50 NIS per visit, which is approximately consistent with the average physician's salary). Similarly, because of imperfect reporting of payments to urgent care centers, we impute their costs based on the average observed rate of 140 NIS per visit. The total cost of services is not very sensitive to these choices because spending on these services accounts for less than 10% of total healthcare spending. To limit the influence of outliers, we winsorized all weekly costs at 100,000 NIS (the 99th percentile of the weekly spending on inpatient care—the most expensive service category).

[7] Note that while the study period spans multiple COVID-19 waves, the public health protocols encouraged patients with suspected COVID-19 symptoms to avoid physician visits and instead visit a mass testing facility for polymerase chain reaction (PCR) or antigen testing: testing, not clinical evaluation was the preferred method for diagnosis. Further, the HMO app had a dedicated channel for locating testing and vaccination facilities (when they became available) and for consultations related to COVID-19.

Appendix Figure A5 compares the distribution of physician actions between the different settings. Device-assisted visits are more likely to include a prescription and much more likely to include antibiotics prescriptions than non-assisted visits by both adopters and non-adopters.[8] Device-assisted visits are much less likely to involve a referral. These differences are merely descriptive, as the choice of setting is endogenous.

3.3. Empirical specifications

The main challenge to identifying the device's impact is that adoption is voluntary and may be influenced by persistent or transient shocks to the patient's health, which may confound the impact of adoption on outcomes. To mitigate this concern, we use a difference-in-differences framework to compare adopter outcomes before and after device adoption against those of matched non-adopters – members who had not used the device by the end of our study period – with similar baseline characteristics, prior utilization patterns, and who visited the same virtual clinic as adopters. Matching on both baseline characteristics and pre-period utilization trajectories aims to reduce concerns that adopters have a different baseline health status. Matching adopters with non-adopters who also had an acute visit aims to reduce concerns that adopters experience different transient health shocks.

To construct the matched sample, we begin with our sample of 28,213 adopters and potential matches of 982,939 regular video visits by non-adopters. Of all potential matches, we select the one most similar to the adopter on baseline characteristics, using nearest neighbor one-to-one matching with replacement. We match exactly on patient gender and on a 9-dimensional vector of indicators for whether the patient had any utilization of a given service in weeks −1 to −4 (week by week) and months −2 to −6 (month by month) relative to the index visit, separately for each outcome. Among these exact matches, we select the nearest neighbor to the adopter in the space defined by the patient's age (in days at the time of the index visit) and ventile of socioeconomic status, using (standardized) Euclidean distance. This matching procedure yields a sample for each outcome consisting of the same set of device adopters and an outcome-specific set of matched non-adopters.[9]

Using our matched samples of adopters and non-adopters, we estimate – separately for each outcome – a flexible event-study model:

$$Y_{itw} = \beta_t Adopter_i + \mu_i + \delta_t + \eta_w + \epsilon_{it}, \tag{1}$$

where i, t, and w index, respectively, individuals, event-time in weeks from the index visit, and calendar week (which account for seasonality in conditions, as well as for COVID-related trends which may affect the propensity to use remote care). Y_{it} is one of several utilization and cost outcomes. $Adopter$ is an indicator for device adoption, which we interact with an indicator for the event-time week. μ_i, δ_t, and η_w denote patient, event-time, and calendar-week fixed effects.[10] We also estimate a more restrictive difference-in-differences specification, which allows us to summarize the impact of adoption with a single parameter γ:

$$Y_{itw} = \gamma Adopter_i \cdot Post_t + \mu_i + \delta_t + \eta_w + \epsilon_{it}, \tag{2}$$

where $Post_t$ is an indicator for whether $t > 0$. We cluster standard errors at the patient level.

A residual concern is that because we do not observe the purchase or delivery of the device, we measure adoption based on the first use of the device rather than its availability. In principle, some of those we classify as non-adopters or future adopters may, in principle, have had the device available but decided not to use it. To the extent that such measurement errors exist, they would bias the estimated impacts of the device toward zero.

4. Results

4.1. Average effect of device adoption

Fig. 1 presents event-study estimates of Eq. (1) for the impact of adoption on the weekly number of primary care visits. Panels A and D of Fig. 2 and Panel A of Table 2 summarize the event-study estimates using the difference-in-differences estimator from Eq. (2) for the impacts on primary care visits. In the year that follows the device adoption, device visits add 3.1 visits per 100 members per week. This increase in device-assisted visits following device adoption is partially – but not completely – offset by a decrease in primary care visits in other remote settings. Over the same period, adopters have significantly *fewer* phone and (deviceless) video visits. The number of in-person visits does not change significantly. Consequently, the total number of primary care visits increases by 2.1, a 12% increase over a pre-adoption baseline of 17.4 visits per 100 members per week. This net increase approximately equals one extra primary care visit per member per year.

[8] Note that since diagnosis quality may vary between settings, differences in the distribution of diagnoses may also reflect misdiagnoses in virtual visits, though our grouping of conditions into broad categories makes it less likely.

[9] There are 8 cases out of 394,982 (that is, 28,213 adopters times 14 outcomes) in which we were unable to find a match, and therefore excluded those visits from the sample.

[10] Note that because the treatment is binary and the comparison group consists of never-treated matched individuals, this setting does not give rise to the problems highlighted by a recent difference-in-differences econometric literature, which arise when either the treatment is continuous or when individual units switch their role from treatment to control during the study period (for a review see Roth et al., 2022). Further note that our estimation approach aligns with the stacked difference-in-differences approach (Cengiz et al., 2019). Specifically, each device adoption can be considered as a separate "sub-experiment". By lining them up in event time with corresponding never-adopters, we essentially stack these sub-experiments to identify the effect of adoption. The fact that adoption occurs once per treated patient in our study ensures that each treated individual contributes only one "sub-experiment" to the stack, simplifying the comparison with never-adopters.

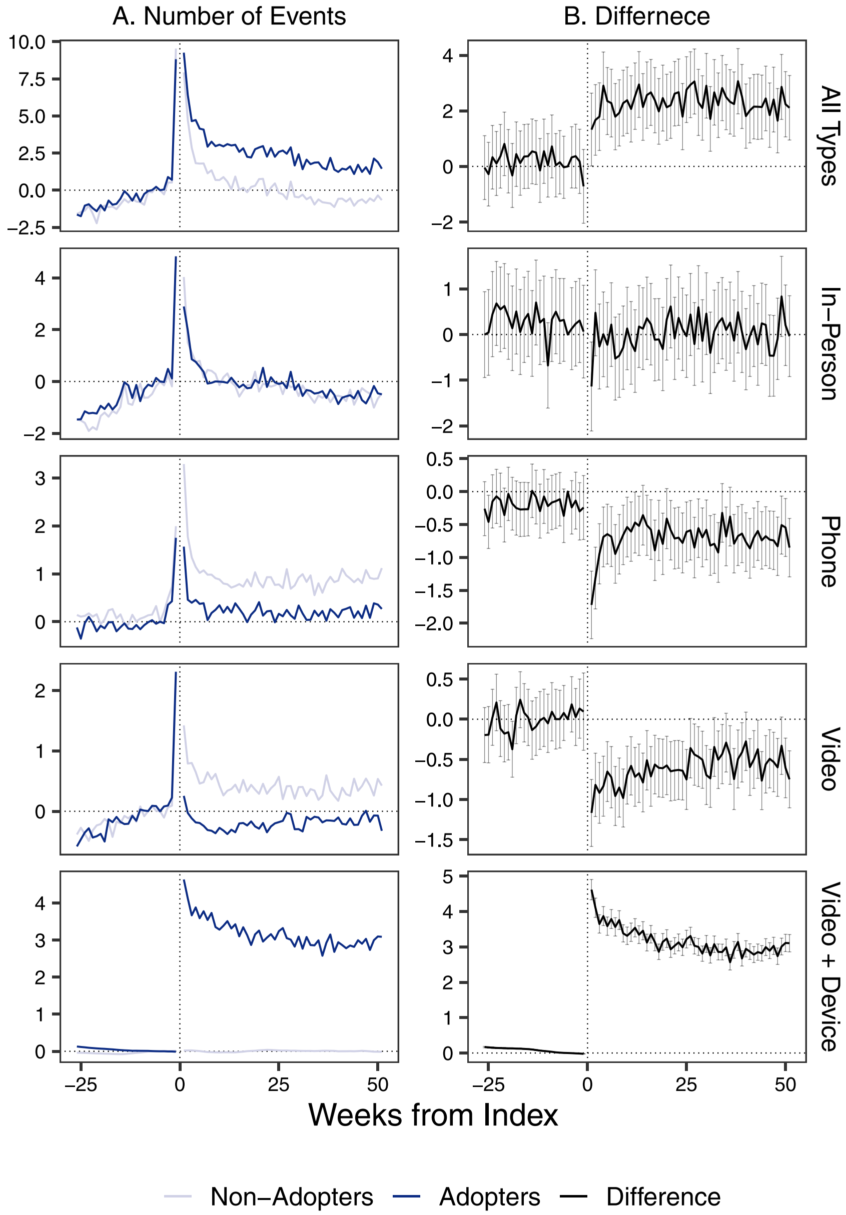

Fig. 1. The impact of device adoption on primary care visits.

Figure shows estimates of the impact of device adoption on adopters' weekly number of primary care visits of different types relative to matched non-adopters. Each row shows results for a different visit type. Panel A shows the mean number of visits (per 100 members), residualized by patient and calendar-week fixed-effects. Panel B shows estimates of β_t from Eq. (1) and their 95% confidence intervals. The vertical dotted line denotes the index week 0, which is excluded. The very slight pre-trend in device-assisted (Video+Device) visits is an artifact of including calendar-week fixed-effects: by definition, there were zero device visits in the pre-adoption period. Section 3 describes variable definitions in detail.

Fig. 3 and Appendix Figure A6 present event-study estimates of Eq. (1) for the impact of adoption on utilization and cost of different types of healthcare services. Panel B of Fig. 2 and Panel B of Table 2 summarize the impacts of adoption on the number of billed encounters, categorized by type of service, in the year following adoption. In contrast to the increased number of primary care visits, the utilization of services in more intensive settings decreases: device adoption results in significant reductions in the use of urgent care centers, ER, and hospital services (with 0.04, 0.17, and 0.05 fewer events per 100 members per week, respectively). All these services decrease by more than 10% of their baseline levels among adopters, with similarly significant reductions in the costs of these services. The use of lab and imaging tests, as well as specialist consults, do not show significant changes. These findings align with the notion that device adoption and the consequent increase in primary care use either substitute for more intensive

Table 2
The impact of device adoption on utilization and cost.

	All				Pediatric Sample				Adult Sample			
	Baseline Mean (1)	Coeff (2)	Stnd Error (3)	% Change (4)	Baseline Mean (5)	Coeff (6)	Stnd Error (7)	% Change (8)	Baseline Mean (9)	Coeff (10)	Stnd Error (11)	% Change (12)
A. Number of Primary Care Visits (per 100 Members per Week)												
All Types	17.39	2.12	0.14	12.2%	20.39	3.04	0.19	14.9%	12.50	1.04	0.20	8.3%
In-Person	12.87	−0.25	0.11	−1.9%	15.70	−0.23	0.15	−1.5%	8.26	0.06	0.13	0.8%
Phone	2.74	−0.51	0.05	−18.6%	2.58	−0.36	0.06	−13.9%	2.99	−0.72	0.09	−24.0%
Video	1.78	−0.61	0.04	−34.2%	2.11	−0.58	0.05	−27.4%	1.25	−0.62	0.07	−49.1%
Video + Device	0.00	3.10	0.03		0.00	3.93	0.05		0.00	1.75	0.04	
B. Number of Events (per 100 Members per Week)												
All Services	36.82	1.68	0.24	4.6%	33.51	3.05	0.27	9.1%	42.21	−0.37	0.46	−0.9%
Primary Care[a]	15.15	1.37	0.12	9.1%	17.68	2.23	0.17	12.6%	11.03	0.35	0.17	3.1%
Drugs	12.91	0.56	0.10	4.3%	11.82	1.18	0.12	10.0%	14.68	−0.30	0.16	−2.0%
Antibiotic	2.24	0.35	0.04	15.6%	2.56	0.39	0.05	15.3%	1.73	0.30	0.05	17.5%
Labs and Imaging	6.45	−0.03	0.09	−0.5%	3.88	0.08	0.07	2.2%	10.62	−0.29	0.21	−2.7%
Specialist	6.35	−0.10	0.10	−1.5%	4.21	0.02	0.10	0.6%	9.81	−0.32	0.19	−3.2%
Urgent Care	0.33	−0.04	0.01	−11.3%	0.39	−0.03	0.02	−6.5%	0.23	−0.05	0.02	−21.1%
ER	0.70	−0.17	0.02	−24.1%	0.60	−0.08	0.02	−13.9%	0.85	−0.30	0.04	−35.0%
Inpatient	0.21	−0.05	0.01	−22.3%	0.14	−0.01	0.01	−10.4%	0.32	−0.10	0.02	−31.0%
C. Cost (NIS)												
All Services	75.20	−5.23	2.63	−7.0%	49.13	−1.52	2.49	−3.1%	117.54	−11.37	5.63	−9.7%
Primary Care	8.07	0.89	0.07	11.0%	9.40	1.41	0.09	15.0%	5.90	0.24	0.10	4.1%
Drugs	14.08	−0.47	1.08	−3.4%	8.64	−0.16	1.25	−1.9%	22.90	−1.00	1.98	−4.4%
Antibiotic	0.30	0.01	0.02	3.4%	0.33	0.04	0.01	12.0%	0.27	−0.03	0.04	−11.8%
Labs and Imaging	9.07	−0.37	0.31	−4.1%	3.75	0.37	0.28	9.9%	17.71	−1.79	0.69	−10.1%
Specialist	5.05	−0.17	0.08	−3.5%	3.01	−0.08	0.06	−2.6%	8.35	−0.37	0.18	−4.4%
Urgent Care	0.47	−0.05	0.02	−11.3%	0.56	−0.04	0.03	−6.5%	0.33	−0.07	0.03	−21.1%
ER	5.56	−1.42	0.18	−25.6%	4.64	−0.63	0.19	−13.6%	7.06	−2.66	0.37	−37.6%
Inpatient	20.32	−4.54	2.10	−22.3%	11.48	−0.11	1.83	−1.0%	34.66	−12.08	4.61	−34.9%
Number of Member-Weeks	4,401,228	4,401,228	4,401,228	4,401,228	2,724,228	2,724,228	2,724,228	2,724,228	1,677,000	1,677,000	1,677,000	1,677,000
Number of Members	56,426	56,426	56,426	56,426	34,926	34,926	34,926	34,926	21,500	21,500	21,500	21,500

Table shows the estimated impact of device adoption on different outcomes, obtained from estimating equation (2) separately for each outcome. Each group of columns shows results for a different subsample: all adopters, pediatric adopters (children under 18), and adult adopters. Different rows show results for different outcomes: the number of primary care visits per 100 members per week by setting (Panel A), the weekly number of billing events for different services per 100 members (Panel B), and the weekly cost per member of different services in New Israeli Shekels (Panel C). Baseline Mean refers to the mean of each outcome among device adopters before first device use. Coeff and Stnd Error are the estimated coefficient and standard error of γ from Eq. (2). % Change is the same coefficient divided by the baseline mean for the same outcome.

[a]Primary care visit count differ slightly between Panels A and B because Panel A measures the number of visits sourced from EMR, and Panel B measures the number of billing events sourced from billing data. Section 3 describes the sample construction and variable definitions in detail.

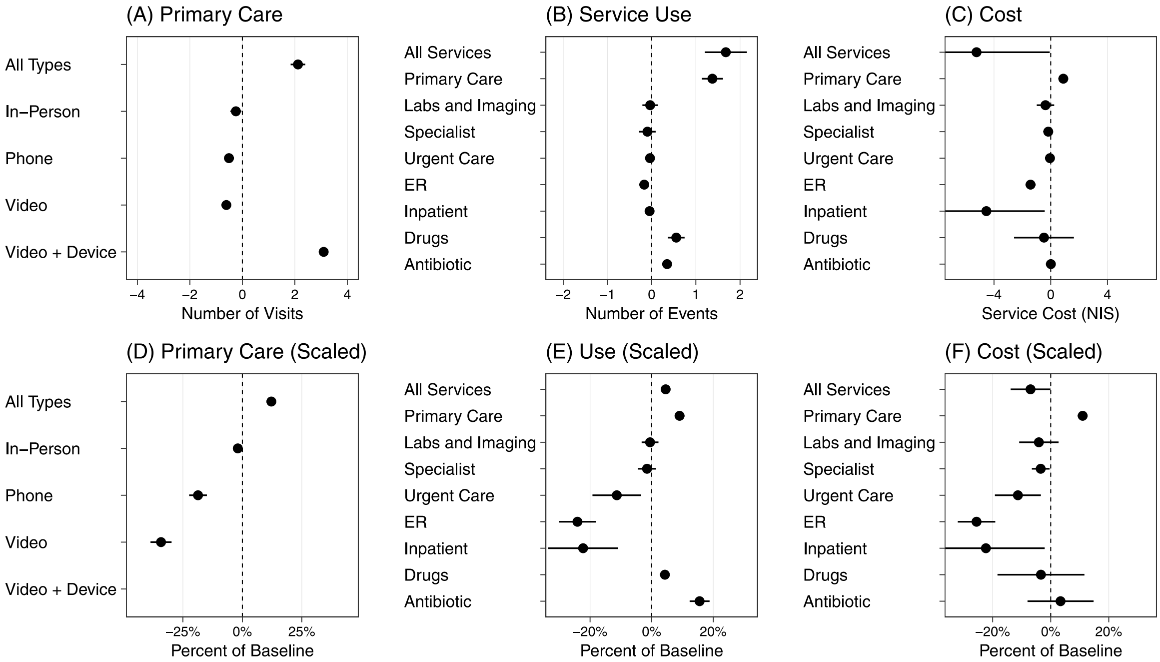

Fig. 2. The impacts of device adoption on utilization and cost.

Figure shows the estimated impacts of device adoption. Each point represents the difference-in-differences estimate of the impact of device adoption (γ from Eq. (2)) for a different outcome. Panels show results for different types of outcomes. The top panels show non-scaled results: the weekly number of primary care visits of each type (per 100 members), the weekly number of billing events for each service (per 100 members), and the weekly total cost per member (in NIS) for different services. The bottom panels show results as percentage of the pre-period mean of each outcome among adopters. Urgent Care refers to urgent care center visits. ER refers to emergency room visits. Section 3 describes variable definitions in detail.

settings or aid in preventing cases from escalating to such settings. Consequently, device adoption does not increase total healthcare costs.

An exception to the overall trend of decreased utilization following device adoption is the observed increase in the use of prescription drugs, particularly antibiotics (the bottom two panels of Fig. 3 and the corresponding summary estimates in Fig. 2 and Table 2). Device adoption correlates with a 4.3% rise in the number of drug prescriptions and a substantial 15.6% increase in the prescription of antibiotics. While this increase in antibiotic use could potentially raise concerns due to the risk of antibiotic resistance, it is also essential to consider that a portion of this antibiotic use may be medically justified, given physicians' ability to examine the patients through the device.[11] This perspective would be consistent with the coinciding reduction in hospital admissions.

Results are robust to key specification choices. Using an alternative measure for utilization, based on whether a patient used any service during the week instead of the number of encounters in a week, yields very similar results (Appendix Figure A7). Recall that to account for time trends in utilization due to COVID-19, we included in our specification patient, location, and calendar-week fixed effects. To further check that extraordinary circumstances do not drive our findings during COVID-19 lockdowns, we conduct a robustness check in which we exclude lockdown periods from the sample (see Appendix B.2 for details). Appendix Figure A8 presents the results, which remain largely unchanged.

4.2. Heterogeneous effects

Adult and pediatric use. Because morbidity and healthcare use depend heavily on patient age, we repeat the analysis separately for adults and children. Appendix Table A3 describes these subsamples of children and adults. Child adopters have a median age of 3 years; half are female. Adult adopters have a median age of 35 years; 63% are female. Fig. 4 and Columns (5) through (12) of Table 2 summarize the results of estimating equation (2) for each of these subsamples separately.

Device adoption has substantially different effects on pediatric and adult adopters. First, adoption impacts the number of primary care visits differently. After adoption, pediatric patients use it more often (3.93 visits per 100 members per week) than adults (1.75 visits per 100 members per week). On the other hand, adults display a more substantial decrease in primary care visits across other

[11] It is difficult to directly classify the appropriateness of antibiotics prescriptions based on visit diagnosis codes because diagnoses may be affected by treatment choices.

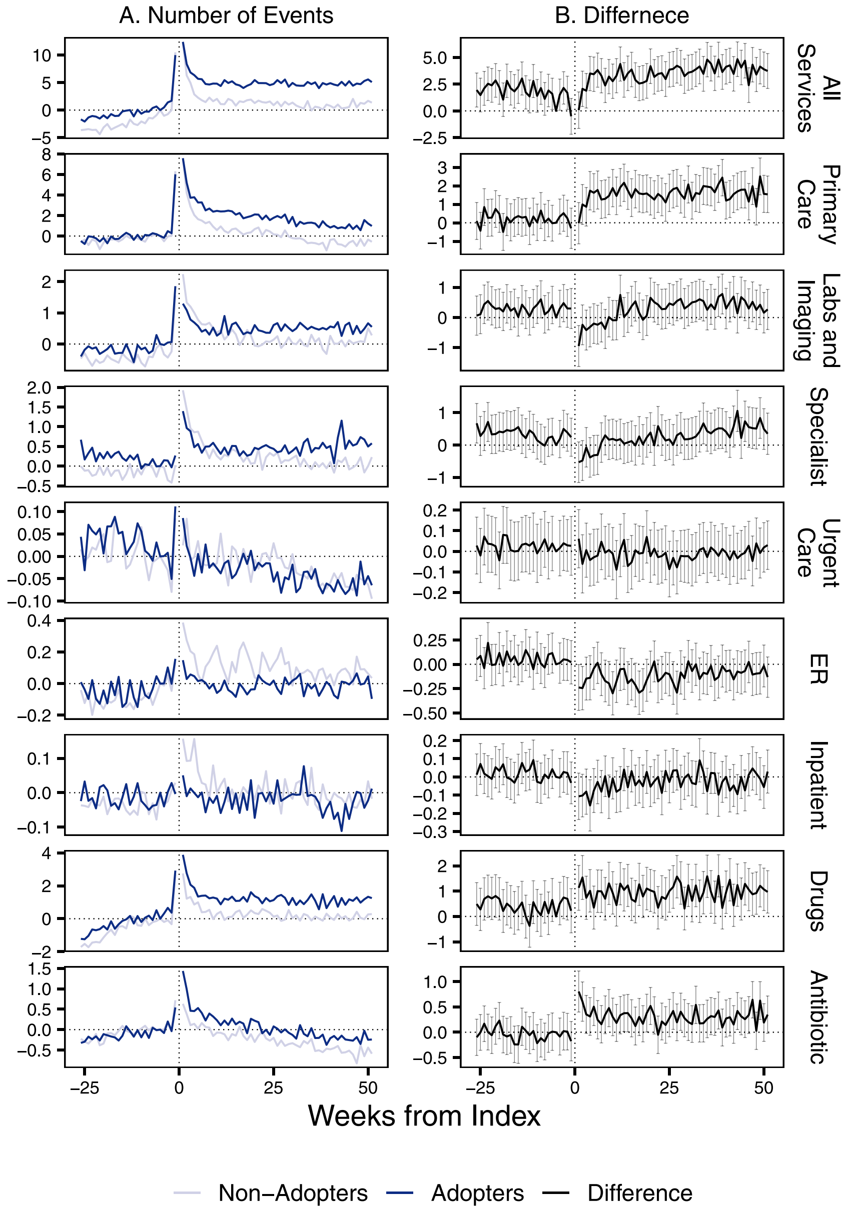

Fig. 3. The impact of device adoption on service utilization.

Figure shows estimates of the impact of device adoption on adopters' weekly number of billed events of different types relative to matched non-adopters. Each row shows results for a different event type. Panel A shows the mean number of events (per 100 members), residualized by patient and calendar-week fixed-effects. Panel B shows estimates of β_t from Eq. (1) and their 95% confidence intervals. The vertical dotted line denotes the index week 0, which is excluded. Section 3 describes variable definitions in detail.

modalities. As a result, the overall increase in the total number of primary care visits across all modalities is more pronounced in the pediatric population, demonstrating a 14.9% rise compared to an 8.3% increase among adults. Second, adults exhibit substantial decreases in the utilization of urgent care centers, ER, and hospital services with respective reductions greater than 20% of their baseline rates, whereas, for pediatric patients, only ER use decreases significantly (by 13.9% relative to the baseline). Similarly, the costs of these services also diminish. While these results are somewhat noisy, they are statistically significant and suggest that impacts diverge between these demographics.[12] In monetary terms, the total cost of care for adults significantly decreases following

[12] We measure adult patients' device adoption based on their first device-assisted visit. However, some of these adults may have initially purchased and used the device for their children's pediatric visits, only to use it for themselves later. As a result, the estimated impacts of device adoption on adult patients may

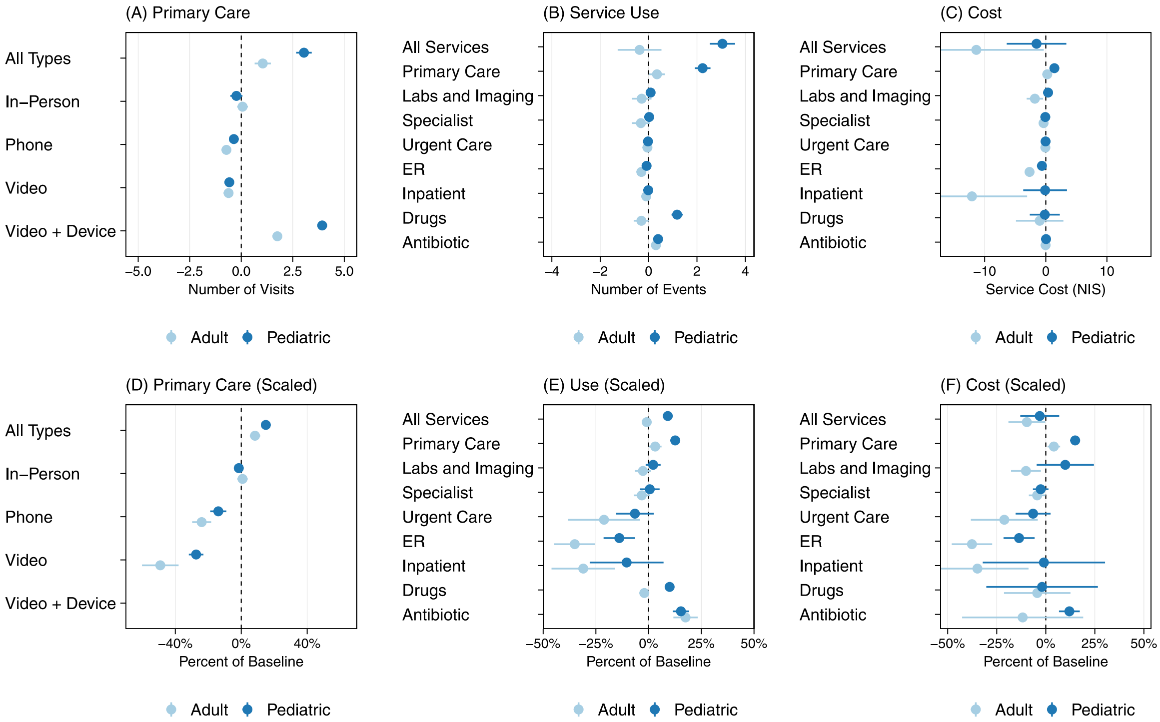

Fig. 4. The impact of device adoption on utilization and cost by age group.

Figure shows the estimated impacts of device adoption separately for pediatric and adult patients. Each point represents the difference-in-differences estimate of the impact of device adoption (γ from Eq. (2)) for a different outcome.Panels show results for different types of outcomes. The top panels show non-scaled results: the weekly number of primary care visits of each type (per 100 members), the weekly number of billing events for each service (per 100 members), and the weekly total cost per member (in NIS) for different services. The bottom panels show results as percentage of the pre-period mean of each outcome among adopters.Appendix Table A3 describes the underlying samples. Table 2 presents the same data in a tabular form.

device adoption by 11 NIS per member per week over the baseline of 118 NIS, a 9.7% reduction. In contrast, the cost of care for children does not significantly change.

Socioeconomic status. To explore the heterogeneity of the impacts of device adoption by patient socioeconomic status, we estimate the model in Eq. (2) separately for patients above and below the median SES. Appendix Table A3 describes these subsamples of high and low SES members. Low-SES device adopters have a slightly greater number of chronic conditions and slightly higher ACG score and prior total cost. Appendix Figure A9 shows the results of this analysis. The reduction in inpatient and total costs is greater for low-SES patients, although the reduction in inpatient admissions is similar across SES groups. Otherwise, we observe no material heterogeneity along this dimension.

Persistence of effects over time. As seen in the bottom panels of Fig. 1, initial device usage spikes in the months immediately following adoption and then stabilizes at a slightly lower rate for the remaining period. This pattern could emerge from transient effects, either due to the novelty of the device or related to care episodes occurring around the device's initial use. To assess the persistence of the device adoption effects, we estimated equation (2) separately across two sequential six-month periods post-adoption (months 1–6 and 7–12). Appendix Figure A10 shows the results. With the exception of device adoption's impacts on inpatient service use and costs, which are greater in the period immediately following adoption, there are no considerable variations in the device's effects on all other services between these periods, implying overall persistent impacts of device adoption.

Correlation across outcomes. Our findings that device adoption leads to both an increase in primary care use and a decrease in urgent and inpatient care are consistent with the hypothesis that the increased primary care visits facilitated by device adoption either replace visits to more intensive settings such as urgent care centers or emergency rooms or reduce such visits by preventing later complications through early diagnosis and treatment. To better understand how the effects on different outcomes are related, we estimate heterogeneity in treatment effects and then examine the correlation in the treatment effects on different outcomes. We do so in two steps. First, we estimate conditional average treatment effects, using the model in Eq. (2) with an interaction between

reflect a mix of potentially heterogeneous effects of two types of adoption: adult adoption following a purchase for personal use or for pediatric use. The same may also apply to pediatric use.

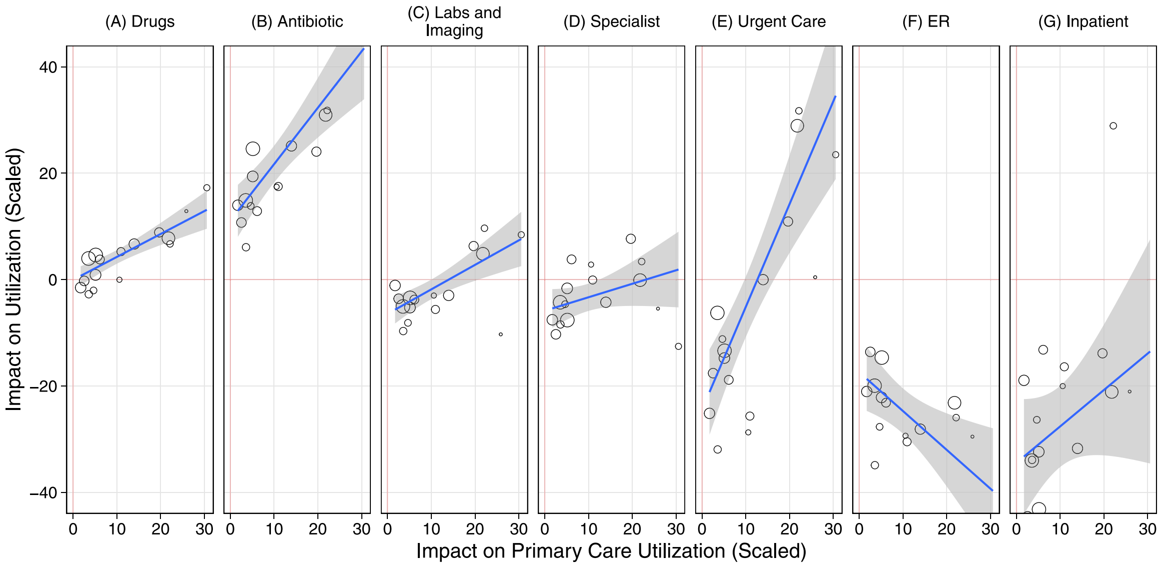

Fig. 5. The association between the impacts on primary care and other services.

Figure shows the results of an analysis in which the impact of device adoption is estimated separately for different groups of patients and correlation across different outcomes (described in detail in Section Section 4.2). Each facet shows an association between the estimated impact on primary care (x-axis) and the scaled impact on a different outcome (y-axis). The impacts are scaled by the baseline (pre-adoption outcome mean among adopters, calculated separately for each subset of the data). Point sizes are proportional to the subgroup sample size. The blue lines and shaded areas are weighted linear regression lines and their 95% confidence intervals. A few outliers that fall outside the plot range are not shown but were included in the calculation of regression lines and confidence intervals.

the main effect of the adoption and an indicator for the interaction of age group, gender, socioeconomic status, and the presence of (any) chronic conditions. Appendix Table A4 describes the size of each subsample resulting from these interactions. We repeat this for each type of service. Appendix Figure A11 describes the estimated distribution of conditional average treatment effects of device adoption on the utilization of different services. Second, using these estimates, we then examine the correlation between conditional average treatment effect on primary care versus other services.

Fig. 5 shows the correlation between the impacts of adoption on primary care use and all other services. The impacts of adoption on primary care are positively associated with its effects on prescription drugs (especially antibiotics), labs and imaging, and specialist services—all of which are directly complementary to primary care. Interestingly, primary care utilization prompted by adoption also shows a positive correlation with the use of urgent care centers but a negative one with ER visits. This may suggest that device-assisted visits can effectively triage cases, particularly for adult patients, directing them towards the more suitable usage of urgent care centers instead of the ER. Finally, while quite noisy, we estimate a positive correlation between primary care utilization and inpatient admissions stimulated by device adoption.

Impacts on hospitalizations by type. In an attempt to gain more insight into the mechanisms driving the reduction in inpatient admissions, we analyzed the impacts of device adoption on different categories of hospitalizations, classifying them as “avoidable” and “unavoidable” as per the definitions in Magan et al. (2008) for adult admissions and Zucco et al. (2019) for pediatric ones (for details, see Appendix B.2). Approximately 20% of all admissions in our study sample were classified as “avoidable” using this methodology. Appendix Table A5 shows the results of this analysis.

Our results indicate reductions across all hospitalization types, with “unavoidable” admissions showing a larger decrease of 41.2% from a baseline mean of 0.16%. “Avoidable” admissions show a 24.7% decrease from a baseline mean of 0.05%. While we observe reductions, we lack statistical power to discern a definite difference by admission type. These results may also reflect the low specificity of the classification of admissions.[13] Taken together, the results do not provide conclusive evidence for a specific mechanism driving the reduction in hospital admissions.

5. Conclusion

We study the impacts of adopting a digital device that allows patients to conduct several medical exams at home as part of telehealth visits. We have three main findings. First, device-assisted telemedicine increases the use of primary care and the share

[13] Our definition of avoidable admissions, which is commonly used in the literature, is based on classifying a small number of common conditions as avoidable and all others as unavoidable based on the main admission diagnosis without further clinical context. Therefore, they likely have high sensitivity but low specificity.

of such care that is done remotely. Second, while the incremental device-assisted visits are partly offset by reduced use of other modes, overall primary care use nonetheless increases. Third, particularly for adults, device adoption is associated with decreases in care in other, more intensive settings. Consequently, adoption is not associated with an increase in the total cost of care.

The increase in utilization brought by device-assisted telemedicine is consistent with earlier findings that show that increased access to telemedicine resulted in greater primary care utilization (Ellegård et al., 2021; Zeltzer et al., Forthcoming). The welfare implications of such an increase appear mixed. The benefit of device use include the convenience of home-based visits, but the incremental increase in overall primary care use and the increase in antibiotics use accompanying it are sources of concern (though the evidence is not conclusive). On the other hand, a reduction in the use and costs of more intensive services, including ER visits, urgent care center visits, and inpatient admissions (particularly among adults), suggest possible gains.

Our study has several limitations. First, our identification strategy does not rely on a clear natural experiment, which could lead to residual endogenous selection post-matching. Second, the majority of device users were children and young adults, limiting the generalizability of our findings to older adult users. Third, we do not identify the specific mechanisms through which device use impacts the use of other services. Fourth, the one-year time horizon we consider makes it difficult to assess the longer-term impacts of device adoption. Finally, the lack of data on health impacts and non-health benefits, such as the convenience of home-based care, makes determining the welfare implications of increased primary care utilization challenging. Exploring the broader health, welfare, and cost impacts of medical devices for remote examinations and patient monitoring remains a promising direction for further work.

Our results have several broader policy implications. First, when considering the reimbursement policies for telemedicine services, including device-assisted visits, it should be acknowledged that greater access may result in increased use (for example, payment parity policies might inadvertently lead to increased expenditure). Second, as more types of medical devices that expand care beyond episodic visits become more popular (including diagnostic devices and remote monitoring devices), they may change the distribution of demand for medical care toward more primary care. In regions with a shortage of primary care providers, this might strain existing healthcare systems and may not generate the same reduction in urgent or emergency care. Finally, our findings of substantial heterogeneity in the impacts of device adoption suggest that targeting specific groups may carry greater benefits than uniform adoption by the entire population.

CRediT authorship contribution statement

Dan Zeltzer: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Liran Einav:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Joseph Rashba:** Data curation, Formal analysis, Visualization, Writing – review & editing. **Yehezkel Waisman:** Conceptualization, Writing – review & editing. **Motti Haimi:** Conceptualization, Writing – review & editing. **Ran D. Balicer:** Conceptualization, Writing – review & editing.

Appendix. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2023.102780.

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