# Multichannel Delivery in Healthcare: The Impact of Telemedicine Centers in Southern India

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Telemedicine is increasingly used across the developing world to expand access to healthcare, to improve outcomes and to reduce costs. One common model is that of telemedicine centers, which are small primary care facilities run by mid-level (non-physician) providers who conduct a preliminary examination and then facilitate a telemedicine visit with a remote physician in real-time. However, the impact of this channel of care delivery – particularly on existing physical healthcare delivery channels – has not been thoroughly examined. We use data from one of the largest tele-ophthalmology implementations in the world to examine this issue. Using a quasi-experimental difference-in-differences approach, we find that opening a nearby telemedicine center generates a 31% increase in the overall network visit rate from the population within 10km of the new center, 62% of which is driven by new patients, suggesting a substantial increase in access. The rate of eye glasses prescriptions to correct for simple refractive errors increases by 18.5%, while the rate of cataract surgery to replace the natural lens in a patient's eye with an artificial lens remains unchanged. The increase in access and treatment rates does not significantly impact the direct costs incurred by patients but reduces their indirect costs (measured as travel distance) by 30% (12km). Finally, we find significant spatial heterogeneity in these effects, which vary with the distance of patients to facilities. These results have important implications for the design of telemedicine networks and the portfolio of healthcare services provided through them.

*Key words*: Multichannel, Healthcare, Telemedicine, Difference-in-differences, Propensity score weighting
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## 1. Introduction

Telemedicine—broadly defined as remote diagnosis and treatment of patients using telecommunications technology—is a promising approach for expanding healthcare access in rural communities of the developing world (World Health Organization 2010, 2016). A common operating model for telemedicine in such settings is a network of primary care centers equipped with telecommunication technology (hereafter *telemedicine centers*) and staffed by low- or mid-level health workers (Dasgupta and Deb 2008, Agrawal 2020). These workers conduct preliminary patient examination, collect vital statistics and facilitate tele-consultation with a remote physician, who may refer the patient to a secondary or tertiary care facility (Kulshrestha et al. 2011, Ng et al. 2009, Mohanan et al. 2016). The cost-effectiveness of this fixed-base telemedicine model depends critically on whether patients utilize the new channel of care as a complement or a substitute to existing physical channels. However, there is currently no evidence on these effects in the context of developing countries (Ekeland et al. 2010, Khanal et al. 2015).

Cross-channel effects have been studied extensively in the retail sector, e.g., Avery et al. (2012), Bell et al. (2018), but they remain largely unstudied in the context of healthcare delivery. Fledgling evidence from the developed world, where telemedicine typically involves direct interaction between the patient and a qualified medical practitioner (without intermediation at a telemedicine center) suggests that the new channel can either substitute for existing channels or complement them via generation of referrals (Bavafa et al. 2018, Ashwood et al. 2017). However, these results are unlikely to carry over to telemedicine in the developing world due to differences in operating model, patients' baseline access to care and financial burden.

In this paper, we seek to address this gap by providing one of the first rigorous evaluations of the impact of telemedicine centers on patients' care seeking behavior in the developing world. Our study setting is the Aravind Eye Care System (hereafter *Aravind*) in Southern India, which is the largest eye care provider in the world (Krasny 2010). In addition to its large scale, several additional aspects of Aravind's operational model make it an ideal research setting. First, Aravind operates an integrated healthcare delivery system (spanning more than 77 primary care telemedicine centers, 6 community eye clinics, and 14 secondary/tertiary care hospitals as of 2019), which allows us to study the cross-channel effects of telemedicine centers. Second, it is one of the earliest adopters of telemedicine and maintains state-of-the-art data management systems thereby enabling a rigorous empirical estimation of the effect of telemedicine centers over time. Third, Aravind actively disseminates its best practices to other organizations across the world as a WHO Collaborating Center (World Health Organization 2011), which enhances the possibility of generalizing our findings through further studies.

For our analysis, we focus on a part of Aravind's network comprised of 19 telemedicine centers linked to their flagship tertiary hospital in Madurai. We construct a rich dataset of over 4.8 million visits from 2.3 million unique patients over almost a decade (Jan 2006—May 2015). We conduct a quasi-experimental difference-in-differences analysis that exploits spatio-temporal variation in the opening of telemedicine centers in this network to estimate their causal impact on patient volume in a "treatment group" of census locations within ten kilometers of each telemedicine center. We employ a two-step approach known as propensity score weighting (Imbens and Wooldridge 2009) to address potential endogeneity in the location of the telemedicine centers.[1] In the first step, we estimate the probability (i.e., propensity score) of a location being in the treatment group using several census and geospatial covariates. In the second step, we use the inverse of this probability to weigh observations from each location in the difference-in-differences model, in an attempt to mimic a randomized experiment.

We find that, on average, the opening of a nearby telemedicine center leads to a net increase in the visit rate to the entire Aravind network (visits normalized by population) by 30.9%, of which approximately 62% consists of new patients. Further, this 30.9% increase is a net effect of an increase in visits to the telemedicine center and a 5.1% decrease in visits to the hospital, which itself is a combination of a substitution effect away from the hospital to the telemedicine center and a complementary effect of referrals from the telemedicine center to the hospital. Excluding previously referred patients, we estimate that approximately 16.8% of the visits to a telemedicine center are substitutes for hospital visits whereas the remaining 83.2% represent an increase in patient use of healthcare services, i.e., they would not have occurred had the telemedicine center not opened. Taken together, these findings provide strong evidence that telemedicine centers substantially increase access for rural patients.

We find that there is considerable heterogeneity in the effects of telemedicine centers depending on the complexity of patients' clinical needs. Patients who need "simple" services such as eye glasses for refractive errors (*general* patients) and who can be treated at either a telemedicine center or a hospital show a much greater increase (47%) in the network visit rate and also a significant decrease (7.1%) in the hospital visit rate. In contrast, patients with more "complex" conditions such as cataract, who can be examined at either channel but eventually require surgery at the hospital, display a smaller increase (25%) in the network visit rate but no significant decrease in the hospital visit rate. Further, these effects also translate into a differential impact on treatments delivered and consequently health outcomes for simple and complex patients. The rate of prescriptions for eye glasses, which are known to significantly improve quality of life (Reddy et al. 2018), increases by 18.5% whereas the rate of cataract surgeries performed remains unchanged.

In addition, we find that the increase in access to care and treatment due to telemedicine centers does not significantly change the direct expenses incurred by patients. However, as expected,

[1] Aravind has a well-defined strategy of opening telemedicine centers in locations that are closer to rural communities with a large catchment population, good transport and telecommunications connectivity. Therefore treatment group census locations which are close to telemedicine centers are systematically different from control census locations that are not.

telemedicine centers significantly reduce the average distance travelled by patients (by $\approx 30\%$ or 11.8km) thereby reducing indirect costs incurred due to travel and lost wages.

Finally, we uncover substantial heterogeneity in the impact of opening a nearby telemedicine center depending on its distance from the patient. Specifically, increases in visit rates to the telemedicine centers and to the overall network are higher for patients located closer to the telemedicine centers than for those that are further away from them. Also, in contrast to the negative effect of telemedicine centers on the overall hospital visit rate, telemedicine centers increase the hospital visit rate from census locations that are close to both a telemedicine center and the hospital, suggesting a potential marketing effect.

Taken together, our results suggest that the benefits of telemedicine are largest for patients with simpler needs. Telemedicine also benefits those further from the hospital through increased substitution, which reduces the indirect costs of visiting a healthcare facility. These findings contribute to the operations management literature on multichannel operations by providing insight into how multiple healthcare service channels with different service capabilities (i.e., ability to treat patients of different types such as general or cataract) interact. Our results have important implications for the design and management of telemedicine networks. For example, the spatial heterogeneity of the impact of telemedicine centers can be used as an input into the optimal design of a telemedicine network to maximize overall impact.

More broadly, our results in conjunction with another recent investigation (Mohanan et al. 2016) highlight the need to consider the role of business models in determining the impact of telemedicine on pre-existing channels. That study found that a well-funded and large-scale social franchisee network of telemedicine centers without vertical integration to a hospital had limited adoption among patients and did not significantly improve its targeted health outcomes in childhood pneumonia and diarrhea. Future work could examine whether the differences in findings are be due to Aravind's pre-existing network of facilities and its reputation in the study region and/or greater integration across Aravind's service channels.

The rest of this paper is organized as follows. We discuss the related literature in §2. We describe our research setting and our econometric approach in §3 and §4, respectively. We present our main results including the heterogeneous effects of telemedicine centers by distance in Section 5 followed by a summary of the main robustness checks in §6. Lastly, §7 contains a discussion of our findings, their managerial implications and limitations.

## 2. Literature Review

A large and rapidly growing literature, as evidenced by multiple systematic reviews, provides mixed evidence regarding the adoption and effectiveness of telemedicine across multiple operational models and patient populations (Dávalos et al. 2009, Ekeland et al. 2010, Wade et al. 2010, Delgoshaei et al. 2017).

On the one hand, some studies find that patients' adoption of telemedicine can reduce hospital admissions. Steventon et al. (2012) conduct a cluster randomized trial of tele-monitoring of patients with chronic conditions (e.g., diabetes, chronic obstructive pulmonary disease, heart failure) across 139 practices England. They find that inpatient admissions and patient mortality (but not emergency admissions and emergency room visits) are significantly lower in the intervention arm compared to the control arm. Grabowski and O'Malley (2014) find that increased engagement of patients with a remote medical team via a video consultation system, reduced hospitalizations in some locations of a for-profit chain of nursing homes in Massachusetts. More recently, Sun et al. (2020) find that adoption of telemedicine by emergency departments (EDs) in the state of New York reduced ED length of stay and waiting times by 15.3% and 9.3%, respectively, which in turn, can lead to better outcomes.

On the other hand, several recent studies question the ability of telemedicine to improve access for under-served populations. Uscher-Pines et al. (2016) did not find significantly higher adoption of a direct-to-consumer tele-health solution (Teladoc) among members of under-served communities (rural locations and locations with health provider shortages) enrolled in the CalPERS Blue Shield of California health maintenance organization (HMO) plan. Ashwood et al. (2017) find that the increased utilization of telemedicine visits did not lead to sufficient substitution for face-to-face visits, thereby increasing the overall costs of healthcare delivery. Bavafa et al. (2018) study the impact of e-visits (e-mail exchanges between patient and provider) using a large dataset from the Veterans Administration health system. They find that introduction of telemedicine increased the number of physician office visits by 6% (rather than reducing them) and decreased new patient visits by 15% thereby reducing access. The authors conjecture that the former effect may be due to limited effectiveness of e-visits to perform a gatekeeping function and the latter may be due to providers responding by rationing their limited capacity.

Telemedicine models in developing countries have received relatively little research attention (Combi et al. 2016, Khanal et al. 2015, Mars 2013). Most of the above evidence is from developed countries, and cannot be readily transferred to developing country contexts owing to key structural differences. First, patients in developing countries have lower baseline access to healthcare services due to extremely limited healthcare capacity. Hence, an identical telemedicine delivery channel is likely to yield a greater improvement in access in a developing country. Second, penetration of health insurance in developing countries is low and patients often pay out of pocket for consultation, medicines and tests as well as indirect costs such as transportation and lost wages which are they are not compensated for. Hence, introduction of telemedicine is likely to result in greater substitution away from traditional channels of care. Third, owing to weaker infrastructure and lower patient awareness, telemedicine models deployed in developing countries are systematically different from those in the developed world. For instance, in developing countries fixed-base hub-and-spoke networks where patients visit a spoke staffed by a mid-level paramedic, who facilitates telecommunication with a qualified clinician at the hub, are far more common than direct-to-consumer telemedicine applications on smartphones and personal computers(Agrawal 2020, Ramdas and Swaminathan 2021). Hence in these settings, the magnitude of improvement in access and substitution away from traditional channel will depend on how far a telemedicine center is from a patient's residence, as well as the actual and perceived quality of care provided by the mid-level provider at the telemedicine center.

Due to the physical nature of the telemedicine centers, our work also relates to the broader literature that empirically examines how multiple physical healthcare delivery channels interact. Bavafa et al. (2022) estimate that improving primary care provider availability can reduce up to 2.4% of non-urgent emergency department visits. Ahuja et al. (2020) find that improved continuity and coordination in patient–provider interactions in primary care reduces inpatient admissions, hospital length of stay and readmissions by up to 2%–4%. Andreyeva et al. (2018) find that one additional minute spent in a home healthcare visit above the average duration reduces the probability of hospital readmission by 8%. However, an important difference between these studies and our work is that they investigate the impact of operational changes in existing channels, whereas we investigate the introduction of a new healthcare delivery channel.

In this regard, our work also shares commonalities with research on introduction of physical channels in omnichannel retail. Bell et al. (2018) examine the role of showrooms in reducing product quality uncertainty in the context of retail sales of eye glasses. They find that showrooms generate increased sales and improve operational efficiency through decreased returns. Avery et al. (2012), find that the addition of a physical retail channel at a retailer with catalog and internet channels cannibalizes sales from the catalog channel in the short term, but increases sales through the catalog and online channels in the long run. They hypothesize that these results could be explained by customers learning about complementary channel capabilities, e.g., being able to physically inspect the products in the store before buying through the online or catalog channels. In our study, we find indicative evidence that the new channel (telemedicine centers) can act as both a complement and a substitute depending on its relative distance to the patient compared to that of the existing channel (hospitals).

## 3. Setting and Data

In this section, we describe the institutional details of our study setting and the operational data used for our analysis.

### 3.1. Institutional Setting

Aravind delivers a wide spectrum of eye care services ranging from primary to tertiary care through an integrated care delivery system spread across the southeastern Indian state of Tamil Nadu. The network consists of multiple health facilities, categorized under three channels of care described below. Clinical as well as non-clinical staff across the entire network are salaried and do not receive any monetary incentives for the quality or quantity of services delivered. The integrated structure of the network, along with availability of large volume, high quality data (International Consortium for Health Outcomes Measurement 2015), makes Aravind an ideal setting to examine cross-channel effects of telemedicine in developing countries. Next, we briefly describe the key components of this delivery system that are most relevant to our analysis.

**Hospitals** are Aravind's main channel for healthcare delivery. As of 2018, it operated 12 hospitals in large urban locations that provided inpatient secondary and tertiary care as well as outpatient primary care for a wide range of ophthalmology conditions. During the year 2017–18, all hospitals together recorded 2,837,517 outpatient visits and 478,028 surgeries(Aravind Eye Care System 2018). Aravind operates a differentiated pricing model, wherein all patients receive identical quality of clinical care but differential quality of non-clinical services and amenities. For instance, patients can pay a higher price to upgrade to a private room with air conditioning. This model allows Aravind to cross-subsidize clinical care for free patients who account for 21.5% of all hospital visits and 51% of surgeries across all hospitals in 2017-2018 (Aravind Eye Care System 2018).

**Vision camps** have been an essential element of Aravind's outreach strategy since Aravind's founding. They are typically one-day events organized in rural communities, where more than 70% of India's population resides (Chandramouli 2011), in collaboration with local community partners. Aravind provides a team of ophthalmologists and support staff from hospitals to deliver clinical services whereas the local partners is responsible for fundraising and marketing activities. Most camps focus on conducting free screening for cataract, which is the most common cause of avoidable blindness globally and in India (World Health Organization 2012). Individuals with operable (i.e., mature) cataracts are offered free corrective surgery and round trip transport to and from the hospital. In addition, camps also conduct basic eye examinations for detecting refractive errors, which are the most common cause of visual impairment (World Health Organization 2012), and sell prescription glasses to correct those at an average price of around ₹300. In 2017–18, Aravind operated around 2,500 camps across the entire network with an average of 230 patients per camp(Aravind Eye Care System 2018). Although camps contribute approximately 30% of cataract surgeries across the entire network, their population coverage is low (Fletcher et al. 1999).

**Telemedicine (vision) centers** were added to Aravind's outreach strategy in 2004 to overcome the low population coverage of vision camps. They are permanent facilities, typically based out of small rented properties ($\approx$ 400–500 sq. ft.) in large villages or small towns with good road connectivity and a catchment population about 50,000 within a radius of five kilometers. Each center is staffed by two personnel (a mid-level ophthalmic technician and a front-office manager) and is connected to one of the hospitals via video conferencing link with an Electronic Medical Record (EMR) in the cloud. Telemedicine centers provide basic aspects of primary eye care such as detection and correction of refractive errors, screening and outpatient management of cataract and diabetic retinopathy, and emergency removal of foreign objects from the eye. The technician conducts preliminary examination of the patient including capture of digital images of the patient's eyes (through the cloud based EMR) and shares the results with an ophthalmologist at the hospital. She then facilitates a real-time tele/video-consultation between the patient and a junior ophthalmologist at the hospital. The ophthalmologist makes the final diagnosis based on the technician's notes, their own clinical examination and the results of the diagnostic procedures, and subsequently prescribes the treatment. Simple treatments, e.g., prescription eye drops, medication and glasses are delivered by the technician at the telemedicine center. Patients who need further advanced diagnostic investigations, treatment or surgery, are referred to the hospital and given referral paperwork to present there, but they have to arrange and pay for their own transportation. Patients are charged a minimal consultation fee of ₹20, which covers up to three visits within a three month period, but diagnostic tests, prescription medicines and glasses are charged for separately. In 2017–18, 586,418 patient visits occurred across 67 telemedicine centers, of which less than 10% were referred to a hospital(Aravind Eye Care System 2018).

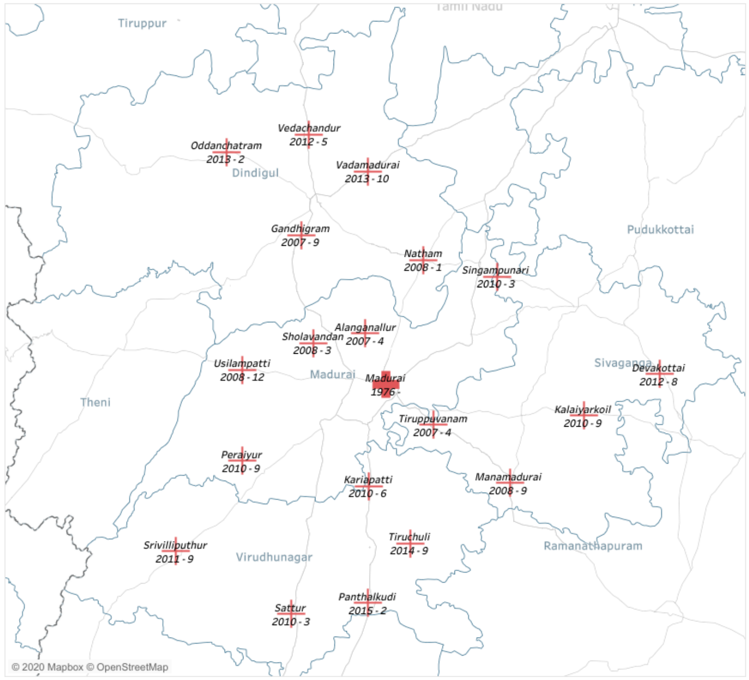
### 3.2. Data

We use data from a subset of the Aravind network comprising their oldest and largest hospital in the city of Madurai and 19 telemedicine centers linked to it that opened between 2006 and 2015, as shown in Figure 1. Below, we provide an overview of three different datasets used in our analysis.

Our **Channel dataset** provides the location and opening date of each facility in the Aravind network as well as the location and date of each of the 1499 vision camps run by the Madurai hospital between January 2006 and May 2015. We use the combination of village and district name of each location to obtain its latitude and longitude using the Google maps API.

Our **Census dataset** contains information on 1,973 census locations in the four local districts of interest (Dindigul, Madurai, Sivaganga, Virudhunagar). Each observation contains the name of the

**Figure 1** **Map showing telemedicine centers in the region around the Madurai Hospital**




**Note:** Map includes the district boundaries and the road network. The thick cross indicates the location of the Madurai hospital, and the thinner crosses indicate the locations of the 19 telemedicine centers affiliated with this hospital. The telemedicine centers' locations and year and month of opening for each facility opened are provided as labels.

village, the sub-district, and the district. The dataset also contains availability of transportation (e.g., bus and rail) and healthcare infrastructure (e.g., number of hospitals, doctors, pharmacies). We use the same geolocation procedure as that for the **channel dataset** to generate the latitude and longitude of each census location. Coordinates for 389 locations, which could not be geolocated by this method, were determined manually by specialists at Aravind. A subset of 1820 non-urban locations were further cross-verified against geolocation data available from a Geographic Information System specialist at a local research institution in India. We use geolocation of each census location to calculate its approximate distance to each of the Aravind treatment facilities and camp locations.[2] We use this augmented census dataset to identify census locations that are within a given distance from a hospital, telemedicine center or camp.

Our **Visits dataset** consists of 4,860,945 patient visits to the above network of facilities between January 2006 and May 2015, made by 2,296,275 unique patients who live in four districts surrounding the Madurai hospital. For each visit, we observe the unique patient identifier[3] along with the

[2] We compute distances using the Haversine formula which computes the straight line, i.e., "as the crow flies", distance between two positions from their latitudes and longitudes.

[3] The unique patient identifier may not be matched perfectly across facilities. This means that some follow-up visits at the hospital following referral from a telemedicine center may not be identified. We conduct several robustness checks for our analysis regarding referrals in §A.7 of the Online Appendix to account for this.

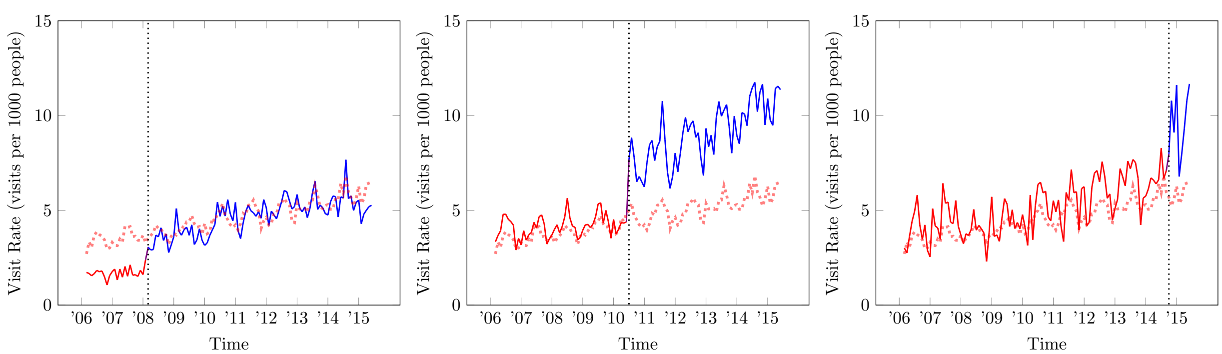
patient's de-identified address (locality, village, town, block/taluk, and district), initial registration date, visit date, facility visited (e.g., hospital or telemedicine center), all medical diagnoses and treatments provided and total financial charges.

We merge the patient visits dataset with the augmented census dataset through a "fuzzy" match between de-identified patient address data and census location names. The details of this procedure are documented in §A.6 of the Online Appendix. Excluding patients with missing or unmatchable data, we are left with 4,665,979 visits (95.76% of the original) from 2,198,878 unique patients (95.99% of the original) that were mapped to 1926 census locations (97.62% of the original) in our dataset. We aggregate the observations in the merged dataset at the census location–month level to create a balanced panel of 217,638 observations (1926 census locations observed over 113 months).

Before delving into the econometric analysis in the next section, we provide some model-free evidence for the impact of telemedicine centers on the number of visits to the entire network for three illustrative telemedicine centers, in Figure 2 below. The subfigures also provide a glimpse into the spatio-temporal variation in the opening of different telemedicine centers, which we exploit in our empirical approach as described below. The full set of figures for all 19 telemedicine centers are provided in §A.4 of the Online Appendix.

**Figure 2 Effect of telemedicine center on monthly network visit rate: Illustrative example**

(a) Natham (b) Kariapatti (c) Tiruchuli




**Note:** The red dotted line represents the average visit rate (per 1000 people) over all control locations (i.e., all census locations that are never within 10km of a telemedicine center). The vertical black dotted line in each subfigure represents the month during which a telemedicine center opened in the village indicated by the subfigure title. The red and blue solid lines represent the average visit rate from treated locations (i.e., all census locations within 10km) of the telemedicine center where the color change from red to blue highlights the contrast before and after its opening.

## 4. Econometric Approach

We use a quasi-experimental differences-in-differences (DiD) approach to estimate the impact of the introduction of telemedicine centers, wherein change in the outcome variable (e.g., network visit rate) in the treatment areas is compared with that in the control areas.[4] However, a simple DiD approach will lead to biased estimates if the choice of telemedicine center locations was not made in a random manner. For instance, Aravind may have strategically chosen the locations to maximize the impact of telemedicine centers. To correct for such endogenous selection of treatment locations, we use a two-stage propensity score weighting procedure. In the first stage, we estimate the propensity (likelihood) of each census location receiving treatment, i.e., being within 10 km of a telemedicine center. In the second stage, we estimate the DiD model on a restricted sample of treatment and control locations with comparable propensity scores, where each observation is weighted by the inverse of the propensity of treatment (IPT). This procedure yields unbiased estimates of the impact of treatment under the assumption that selection into treatment is based only on observables (Hirano et al. 2003); these estimates are also doubly robust, i.e., they continue to remain unbiased even if one of the two stages is misspecified (Imbens and Wooldridge 2009). This procedure has been used recently in multichannel retail settings with similar econometric challenges (Bell et al. 2018).[5]

### 4.1. First stage: Modeling endogenous selection of telemedicine center locations

To address the concern of endogenous selection of telemedicine center locations, we develop the following cross-sectional logistic regression model, given by (1), to predict the probability of census location $i$ being selected into treatment, i.e., of receiving a telemedicine center within ten kilometers by the end of our study period ($P_i$):

$$\log\left(\frac{P_i}{1-P_i}\right) = \theta_0 + \theta_1 N_i + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\gamma}\mathbf{D}_i \tag{1}$$

The independent variables in this model are based on our institutional knowledge regarding Aravind's criteria for choosing telemedicine center locations. By Aravind's criteria, a telemedicine center must: (i) have a large population and serve as a hub for the nearby villages, (ii) have good road connectivity, and (iii) neither too close nor too far from any existing Aravind facility. We construct variables using the augmented census dataset described in §3.2. Accordingly, $\mathbf{X}_i$ denotes a vector of covariates, which includes the population of the census location $i$, indicators for the presence of a major road within $0-5$ km and $5-10$ km from location $i$, and indicators for proximity

[4] Figure 5 provided in §A.4 of the Online Appendix provides a map depicting the treatment and control locations.

[5] We note that using weights derived from a coarsened exact matching method produces qualitatively similar results that are available upon request to the authors.

of location $i$ to the Madurai Hospital in 4 discretized sets from $0-25$ km, $25-50$ km, $50-75$ km and $>75$ km. In addition, we include $N_i$, which denotes the number of potential telemedicine center locations within ten kilometers of the focal location $i$ that have a population of 40,000 or more within five kilometers, have a major road within 5 km and are not within 15 km of the hospital in Madurai or within 10 km from the surgical hospital in Dindigul.[6] It captures the intuition that the chances of a focal location $i$ being within ten kilometers of a telemedicine center increases if there are more potential telemedicine center locations in its vicinity, e.g., due to a greater population and better roads in the nearby locations. Finally, $\mathbf{D}_i$ denotes a set of district fixed effects for each census location $i$. Descriptive statistics for these and additional variables from the census dataset are provided in §A.2 of the Online Appendix.

**Table 1 Propensity Score Model for selection of census locations into treatment**

| | (1) Telemedicine Center [0-10km] |
|---|---|
| No. of Potential TC locations within 10km | $1.16^{***}$ (0.01) |
| Population (1000s) | $0.97^{***}$ (0.01) |
| Road Proximity | |
| [0-5km] | $1.67^{*}$ (0.39) |
| [5-10km] | $1.58^{\dagger}$ (0.39) |
| Hospital Proximity | |
| [25-50km] | 1.21 (0.19) |
| [50-75km] | 0.82 (0.16) |
| [75+km] | $0.29^{***}$ (0.07) |
| District FEs | Yes |
| Observations | 1973 |

Odds Ratios shown, with standard errors in parentheses.
$^{\dagger}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 1 shows the odds ratios for the model, which are directionally consistent with Aravind's stated selection criteria. Each additional potential telemedicine center location within ten kilometers of the focal census location increases the odds of it being "treated" by 16%. Similarly, increase in population of location $i$ by 1000 decreases the odds ratio of it being selected for treatment by 3.3% indicating Aravind's preference for rural locations (which typically have lower population compared to urban ones). Further, having any major road within 5 km or $5-10$ km increases the

[6] For the identification of potential locations, we use the count of locations with more than 40,000 inhabitants within 5km, instead of 50,000 as stated by Aravind. We choose 40,000 because it offers a marginal improvement in the discriminatory power of the model (measured as AUC of the ROC curve) and is consistent with the idea that telemedicine centers should have a large surrounding population. We get qualitatively similar results if we use 50,000 inhabitants as the cut off.

odds of being in the treatment group by 67.4% and 58.3%, respectively, compared to locations that are more than 10km away from a major road. Finally, being more than 75 km from an Aravind hospital decreases the odds ratio of being in the treatment group by 70.6%. We also find that this model provides reasonable fit with the data (AUC=0.733).

We verify the validity of our propensity score weighting approach by checking if systematic differences in covariates of interest across two groups can be removed by: (i) restricting the sample to the region of *common support* (i.e., to values of propensity score over which the distributions for the treatment and control group overlap), and (ii) weighting the observations in the treatment and control groups by the inverse of the propensity of treatment (IPT) (Hirano and Imbens 2001).[7] Following Bell et al. (2018), we separately regress census location covariates against the treatment group indicator variable, both unweighted over the full sample of locations as well as weighted by IPT on the sample within *common support*. Figure 3 shows that all statistically significant differences in the covariate means between the treatment and control groups in the full sample (e.g., the number of potential telemedicine centers locations, distance from the hospital, the number of health centers, and area in sq. km.) are eliminated by our first stage procedure comprising the two steps described above.

### 4.2. Second stage: estimating the impact of telemedicine centers

In the second stage, using the restricted sample within common support and IPT weights, we estimate the impact of telemedicine centers using generalized Difference-in-Differences (DiD) models of the form:

$$Y_{it} = \alpha_i + \gamma_t + \delta TC_{i,t} + \lambda_1 \mathbf{Camp}_{i,t} + \lambda_2 \mathbf{Camp}_{i,t-1} + \boldsymbol{\beta}\mathbf{X_{i,t}} + \epsilon_{i,t}, \qquad (2)$$

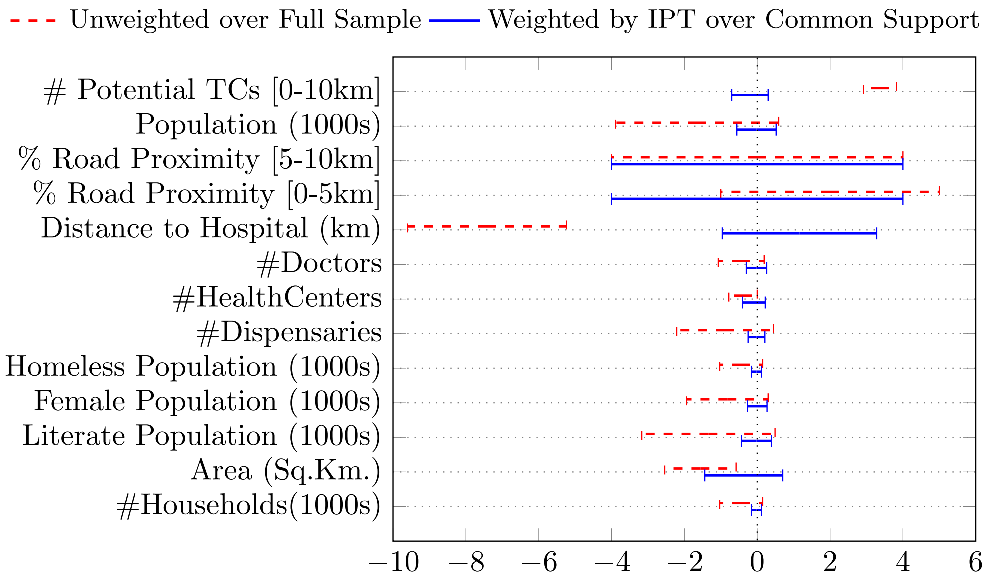
where $Y_{it}$ denotes three different sets of outcome variables of interest.

The first set pertains to patients' use of healthcare services. We define the network visit rate from census location $i$ in period $t$ as the total number of patient visits to a telemedicine center or the hospital from location $i$ in period $t$ per 1000 residents (i.e., divided by the population of location $i$ in thousands).[8] We define visit rates to the telemedicine centers and to the hospital in a similar way. We also compute a modified version of the hospital visit rate, excluding all subsequent visits by patients referred by a telemedicine center. Finally, we also define additional outcome measures

[7] Restriction of the sample to the region of *common support* ensures that each location in the treatment group has at least one comparable counterpart in the control group (and vice versa); this step reduces the sample from 1973 to 1728 census locations. Weighting aims to mimic random sampling by giving greater weight to control (treatment) observations with high (low) propensity of treatment compared to control (treatment) locations with low (high) propensity of treatment.

[8] This measure has an additional advantage of incorporating heterogeneity of the treatment effect by population of the census location (Galiani et al. 2005).

**Figure 3 Covariate Balance**




**Note:** Each bar represents 95% confidence interval for the difference in the mean of each covariate between the treatment and control group. The red bars display the results for the unweighted full sample, while the blue are for the sample over common support when weighted by IPT.

for visits by new and returning patients and for visits by patients who are in different clinical groups (based on their diagnoses).

The second set of outcome variables provide proxies for health benefits or outcomes of patient visits. For this purpose, we calculate prescription rates of eye glasses and cataract surgery rates as these treatments are known to significantly improve patient vision and quality of life.[9]

The third set of outcome variables focuses on direct and indirect costs to patients. For the former, we use the rate of financial charges incurred (i.e., sum of charges incurred by all patients in a census location, in a given month, divided by its population in thousands) whereas for the latter we use average distance travelled by patients to access health facilities in the network.

The main independent variable of our interest is $TC_{i,t}$, which takes the value of 1 if census location $i$ is within 10 km of an open telemedicine center in period $t$.[10] Thus, $\delta$ can be interpreted as the change in the outcome variable after a telemedicine center opens nearby relative to what would have occurred if it had not. We include additional variables to control for other aspects of the Aravind network that change over time and across locations and whose impact may differ across the treatment and control groups. For instance, as described earlier, vision camps are part

[9] For instance, Reddy et al. (2018) find that providing glasses to tea pickers with age-related visual impairment increased their daily productivity by 21.7% and, consequently, their incomes which include volume-based incentives.

[10] For parsimony, in our main model we exclude controls for the potential spillover of the impact of telemedicine centers beyond 10km. This exclusion produces conservative estimates of the treatment effect, i.e., yield smaller absolute value of difference-in-difference estimates. However, in our case, including such spillover effects does not substantively alter our results and extended analysis of spillover effects is available upon request to the authors.

of Aravind's outreach strategy and are likely to impact patient visits and treatments. Moreover, the intensity of camp activity may differ in locations that are closer to the telemedicine centers. To account for this, we use a categorical variable $\mathbf{Camp}_{i,t}$ that denotes whether one or multiple camps were organized within 10 km of location $i$ in period $t$. We also include $\mathbf{Camp}_{i,t-1}$ to account for lagged marketing effect of camps, e.g., patients screened in camps this month follow up at the hospital for treatment or surgery in the next month Gupta et al. (2018).

We include additional control variables, $\mathbf{X_{i,t}}$, to account for the opening of other Aravind facilities during our observation period whose catchment area may overlap with the census locations in our study districts but whose visits are not included in our dataset.[11] Specifically, for each census location $i$, we consider concentric rings of radius up to 30 km and 15 km (in equal increments of 5 km) around each relevant secondary hospital and telemedicine centers, respectively. We then construct a vector of indicator variables to denote whether location $i$ is within one of the rings around a given open facility in period $t$. Descriptive statistics for all variables used in the DiD models are included in §A.2 of the Online Appendix.

Census location fixed effects $\alpha_i$ represent all time-invariant factors such as distance to the hospital, road connectivity, population and demographics, as well as the average effect of all time-varying factors within a location.[12] Similarly, time fixed effects $\gamma_t$ include all location-invariant factors such as seasonality and general increases in awareness about eye care in the population, secular improvement in road and transport infrastructure, increases in income and wealth levels. These are partly reflected in the upward trend in visit rates in Figure 2. Lastly, we estimate two-way clustered standard errors (Cameron et al. 2011) to allow for correlation in errors ($\epsilon_{it}$) over month and census location.[13]

## 5. Results

We begin this section with estimates of the average impact of telemedicine centers on visit rates for all patients (§5.1), immediately followed by estimates of differential impact on new vs. returning patients (§5.2) and on simple vs. complex patients (§5.3). We then provide estimates of the impact on treatment rates (§5.4) and direct and indirect costs (§5.5). Finally, we provide evidence for heterogeneity in the impact of treatment depending on patients' distance to the nearest telemedicine center as well as the hospital (§5.6). For each of these, we estimate the impact on the overall network

[11] These include a secondary surgical hospital in Dindigul and two facilities in Theni district.

[12] The only relevant census data in India during the timeframe for our study is from 2011, this prevents the inclusion of census location covariances as these would be co-linear with the location fixed effects. We allow for census location specific time-trends in the robustness checks to account for differential unobserved time patterns. Our results are provided in Table 7 in §A.1 of the Online Appendix, and remain qualitatively unchanged.

[13] Our results are robust to clustering at the level of sub-districts or telemedicine centers instead of census locations (see §6.4 for details).

as well as both the telemedicine centers and hospital. For parsimony and clarity, we relegate the estimates of control variables, excluding fixed effects of the 1628 locations and 112 time periods, to Table 24 in §A.3 of the Online Appendix.

### 5.1. Overall visit rates

Intuitively, the opening of a telemedicine center should reduce the indirect costs of accessing care (e.g., time and travel) for patients who live in its proximity. However, the net effect of this reduction on patients' visit rates to the healthcare network is not obvious. Some patients may merely substitute visits to the hospital with those to the telemedicine center thereby not changing the overall visit rate to the network. Other patients, who were unable to bear the indirect cost of visiting the hospital, may access care at the telemedicine centers thereby increasing the visit rate to the network without affecting those to the hospital. Also, lower indirect costs may lead some patients to increase the number of visits. Finally, telemedicine centers may also lead to hospital referrals, i.e., there could be cross-channel complementarities.[14] To uncover the effects of telemedicine centers, we consider outcome variables corresponding to four variants of the visit rates in our DiD model: (i) across the network, (ii) at a telemedicine centers, (iii) at the hospital, and (iv) at the hospital excluding referrals from telemedicine centers. Estimation results are shown in Table 2.

**Table 2 Network and Channel Specific Monthly Visit Rates per 1000 people**

| | (1) Network | (2) Telemedicine Center | (3) Hospital | (4) Hospital (excl. referrals) |
|---|---|---|---|---|
| Telemedicine Center [0-10km] | 2.03$^{***}$ | 2.32$^{***}$ | -0.28$^{*}$ | -0.39$^{***}$ |
| | (0.23) | (0.21) | (0.11) | (0.11) |
| Observations | 186552 | 186552 | 186552 | 186552 |
| Adjusted $R^2$ | 0.718 | 0.499 | 0.735 | 0.734 |

All regressions include location and time FEs, as well as variables for camps, and controls as given by equation (2).
Two-way Clustered Standard Errors (Census Location i, Period t) shown in parentheses.
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

Column (1) shows that the opening of a telemedicine center increases the monthly network visit rate by 2.03 visits per 1000 persons in treatment locations, compared to the counterfactual outcome if the telemedicine center had not opened. To understand the operational significance of this effect, we use our model estimates to predict the average network visit rate for treatment locations with

[14] Opening of telemedicine centers may also have a marketing effect and may increase the hospital visit rate above and beyond referrals. To that extent, our estimate of the substitution effect should be interpreted as net of this marketing effect. We expect substitution to be the dominant of the two effects because the indirect costs of time and travel for visiting telemedicine centers are likely to be much lower than those for visiting the hospital. We exploit the heterogeneity in patients' distance from telemedicine centers and hospitals to further investigate this issue in §5.6.

and without a telemedicine center. For the last 12 months of the observation window these are 8.64 and 6.61, respectively indicating a 30.9% increase in the monthly visit rate.[15] In summary, telemedicine centers resulted in both a statistically significant and operationally significant increase in patients' use of healthcare across the network.

Columns (2) and (3) show the decomposition of the impact across the telemedicine center and hospital channels. We see that opening of a telemedicine center increases the monthly visit rate to the telemedicine channel by 2.32 but decreases the visit rate to the hospital by 0.28, indicating a net substitution effect from opening telemedicine centers. This effect translates to a 5.1% reduction in the number of hospital visits per month from treatment locations. Column (4) shows that the substitution effect is 0.39 (after excluding referrals from telemedicine centers to the hospital), which corresponds to a 7.0% reduction in hospital visits. This estimate, which is not significantly different from that with referrals, provides a more accurate reflection of substitution. Thus, 16.8% (0.39/2.32) of the increase in the telemedicine center visit rate is driven by substitution. In other words, an estimated 83.2% of the increased visit rate corresponds to visits that would not have manifested themselves in the absence of telemedicine centers.

### 5.2. Visit rates for new and return patients

The above findings establish that opening of telemedicine centers leads to significant expansion in the use of Aravind's services. However, this is likely the combined effect of an increased number of visits from returning patients as well as an increase in the number of new patients. Disentangling these two effects is important because the latter is a more appropriate measure of telemedicine centers' ability to improve access to the previously unreached patient population.

**Table 3 New and Return Patient Monthly Visit Rates per 1000 people**

| | Network | | Telemedicine Center | | Hospital | |
|---|---|---|---|---|---|---|
| | (1) New | (2) Return | (3) New | (4) Return | (5) New | (6) Return |
| Telemedicine Center[0-10km] | 1.26*** | 0.77*** | 1.43*** | 0.89*** | -0.16** | -0.12 |
| | (0.12) | (0.13) | (0.12) | (0.09) | (0.05) | (0.07) |
| Observations | 186552 | 186552 | 186552 | 186552 | 186552 | 186552 |
| Adjusted $R^2$ | 0.561 | 0.637 | 0.429 | 0.432 | 0.558 | 0.644 |

All regressions include location and time FEs, as well as variables for camps, and controls as given by equation (2). Two-way clustered standard errors (Census Location i, Period t) shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[15] Given the increase in visit rate over time, focusing on the last 12 months gives us a conservative estimate of the effect size.

Table 3 shows the results obtained by estimating our DiD model separately for visits made by new and returning patients in columns (1) and (2), respectively. We find that the monthly network visit rate for both new and returning patients increases significantly by 1.26 and 0.77, respectively. These constitute 62.1% and 37.9%, respectively, of the overall increase of 2.03 in the network visit rate reported in column (1) of Table 2. To put this in context, we note that the proportion of new patient visits across the entire dataset is 47.4%. The contribution of new and returning patients to the increase in the telemedicine center visit rate is similar to that for the network visit rate. Furthermore, the impact on the hospital visit rate is negative for both new and returning patients but it is slightly larger in magnitude and statistically significant for new patients. These comparisons provide further support for the finding that telemedicine centers do improve access to care in segments of the population that were underserved by the existing care channels.

In contrast to these results, Bavafa et al. (2018) find that e-visits increase physical office visits by 6%, perhaps indicating that they are less appropriate substitutes compared to telemedicine center visits. They also find a decrease in new patient visit rates by 15%, which they argue is due to providers rationing capacity by limiting new patient enrolment to accommodate the greater number of office visits by patients. Surprisingly, we do not find evidence of such rationing in our context even though capacity is thought to be constrained. This may be due to the fact that compared to an individual physician, Aravind facilities are able to absorb increases in volume due to economies of scale.

### 5.3. Visit rate by clinical group

Telemedicine centers have limited capability and can offer a limited portfolio of services compared to the hospital. For instance, glasses can be prescribed and delivered to patients at the telemedicine centers as well as the hospital but surgeries can be conducted only at the hospital. As a result, "simple patients" may be more willing to substitute their hospital visits with those to the telemedicine centers. Furthermore, owing to significantly lower direct and indirect cost of access, patients with minor ailments who did not visit a hospital (despite its capability to treat them) may be willing to visit a telemedicine center. Consequently, the effects of telemedicine centers identified so far – overall increase in usage of healthcare and substitution of hospital visits – may differ across "simple patients," who can be appropriately diagnosed and treated at the telemedicine centers and "complex patients" who cannot be.

To investigate this issue, we focus on visits corresponding to the two largest clinical groups at Aravind. First, the *General* clinical group includes visits for "simple" eye problems such as refractive errors. These can be corrected with prescription glasses and account for approximately 36% of visits across the network. Second, the *Cataract* clinical group includes visits for cataract, which is a comparatively more "complex" condition. These need a corrective surgery and account for approximately 42% of visits across the network.[16] These two conditions are also leading causes of visual impairment and avoidable blindness globally (World Health Organization 2012, 2014), of which over 90% of untreated cases occur in developing countries. Therefore, we aim to understand the extent to which telemedicine centers can successfully address these specific global health challenges.

**Table 4 Clinical Group Monthly Visit Rates per 1000 people**

| | General Patients | | | Cataract Patients | | |
|---|---|---|---|---|---|---|
| | (1) Network | (2) Telemed. Center | (3) Hospital | (4) Network | (5) Telemed. Center | (6) Hospital |
| Telemedicine Center [0-10km] | 1.14*** | 1.27*** | -0.13** | 0.75*** | 0.86*** | -0.11 |
| | (0.11) | (0.10) | (0.04) | (0.12) | (0.09) | (0.06) |
| Camps[0-10km]: One | 0.01 | -0.02 | 0.02 | 0.22*** | -0.01 | 0.23*** |
| | (0.02) | (0.01) | (0.02) | (0.03) | (0.01) | (0.03) |
| Camps[0-10km]: Two+ | 0.06 | -0.03 | 0.09 | 0.36*** | -0.01 | 0.38*** |
| | (0.05) | (0.03) | (0.06) | (0.07) | (0.02) | (0.07) |
| Observations | 186552 | 186552 | 186552 | 186552 | 186552 | 186552 |
| Adjusted $R^2$ | 0.560 | 0.464 | 0.561 | 0.531 | 0.379 | 0.524 |

All regressions include location and time FEs, as well as variables for camps, and controls as given by equation (2).
Two-way clustered standard errors (Census Location i, Period t) shown in parentheses.
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

Table 4 shows the estimates of our DiD model for visits belonging to the general and cataract clinical groups for the network and for separate channels. Columns (1) through (3) show that opening a telemedicine center increases the monthly visit rate of the general clinical group by 1.14 in treatment locations, through an increase of 1.27 at the telemedicine centers (denoting expanded access) and a decrease of 0.13 at the hospital (denoting substitution). These correspond to a 47% increase in the visit rate to the network over the last 12 months of our observation window (from 2.42 to 3.56) and a 7.1% decrease in the hospital visit rate (from 1.83 to 1.70) over the same time period. The decrease in general-patient visits to the hospital channel is similar to a gatekeeping effect (Shumsky and Pinker 2003, Freeman et al. 2016) where telemedicine centers help to ensure that the patients who can be taken care of at a lower capability (and perhaps lower cost) channel do not have to reach a higher capability (and perhaps higher cost) channel. However, in this case it may be driven by patient choice of channel as opposed to provider referral decisions. The effects on cataract visit rates, shown in columns (4) through (6), show that opening a telemedicine center

[16] We use diagnosis codes received by patient during their visit to determine their clinical groups. Patients with diagnosis codes corresponding to refractive errors and cataract are accounted for in both clinical groups.

increases the network visit rate of the cataract clinical group by 0.75, through an increase of 0.86 in the telemedicine center channel and a decrease of 0.11 in the hospital channel, although the latter is not statistically significant. These correspond to a 24.9% increase at the network level and 3.9% reduction (although statistically insignificant) at the hospital.

Next, we compare the impact of opening a nearby telemedicine center on the visit rate of cataract patients, with that of camps (which have been traditionally used to screen and refer cataract patients for surgery). Table 4 shows that organizing one camp increases the monthly visit rate of cataract patients from a location by 0.22 in the month of the camp.[17] At an average frequency of approximately three camps per year, this translates to an increase of 0.66 in the annualized visit rate, which is substantially lower than the annualized impact of a telemedicine center ($0.75\times12 = 9$). Finally, the impact of camps on general patients is operationally negligible and statistically insignificant.

In summary, these results provide several important insights regarding the differential impact of telemedicine centers across clinical groups and relative to camps. First, the increased use of healthcare due to opening of telemedicine centers is much greater for "simple" (general) patients compared to "complex" (cataract) patients. Second, while the substitution effect is significant for "simple" patients it is not significant for "complex" patients. These findings are consistent with the limited capabilities of the telemedicine centers. Third, perhaps surprisingly, even for "complex" patients, the impact of telemedicine centers is an order of magnitude greater than that of camps, when calculated over an equivalent timeframe. This finding highlights the value of providing continuous service provision through a permanent health facility in a community, over and above intermittent service provision through temporary channels.

### 5.4. Treatment rates

Increased use of healthcare services due to the opening of telemedicine centers may not automatically translate into better population level health outcomes. First, the healthcare system may not have the capability to correctly identify patient needs and deliver appropriate treatments. Second, the increased use may be driven by healthier patients, who are more willing to travel to a telemedicine center than to a hospital due to the lower direct and indirect costs. To address this issue, we analyze the impact of telemedicine centers on the provision of appropriate treatments for general and cataract patients, measured by the rate of prescription of glasses and cataract surgeries, respectively.

Column (1) of Table 5 shows that the opening of a nearby telemedicine center increases the rate of glasses prescription in treatment locations by 0.19. This corresponds to an 18.5% increase for

[17] About 2.2% of location-month observations in our data have two or more camps. In those cases, the visit rate increases by 0.36.

**Table 5 Monthly Treatment Rates for general and cataract patients**

| | Glasses Prescriptions | | | Cataract Surgery |
|---|---|---|---|---|
| | (1) Network | (2) Telemedicine Center | (3) Hospital | (4) Hospital |
| Telemedicine Center [0-10km] | 0.19*** | 0.31*** | -0.12*** | 0.02 |
| | (0.04) | (0.03) | (0.03) | (0.02) |
| Camps[0-10km]: One | 0.00 | -0.01 | 0.01 | 0.19*** |
| | (0.01) | (0.00) | (0.01) | (0.02) |
| Camps[0-10km]: Two+ | 0.04 | 0.00 | 0.04 | 0.23*** |
| | (0.03) | (0.01) | (0.03) | (0.03) |
| Observations | 186552 | 186552 | 186552 | 186552 |
| Adjusted $R^2$ | 0.441 | 0.291 | 0.441 | 0.183 |

All regressions include location and time FEs, as well as variables for camps, and controls as given by equation (2).
Two-way clustered standard errors (Census Location i, Period t) shown in parenthesis.
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

the last 12 months in the observation window, which is substantially lower than the increase of 47% in the visit rate of patients in the general clinical group. Further, columns (2) and (3) shows the decomposition of this overall increase across two channels. We see a significant increase of 0.31 in the prescription rate through the telemedicine center channel and a significant reduction of 0.12 at the hospital, representing substitution. This reduction is very close, in absolute terms, to the reduction in the hospital visit rate observed for patients in the general category. However, in relative terms the decrease of 0.12 in the rate of glasses prescription translates to a reduction of 12.3% (from 0.942 to .826), almost double that for the general clinical group visit rate. Taken together, these results point to a couple of valuable insights. First, telemedicine centers indeed increase provision of a simple treatment, i.e., provision of glasses, that can significantly improve quality of life of low-income rural populations, as reported by Reddy et al. (2018). Second, a large part of the increased use of care at telemedicine centers is driven by healthier patients, who do not need glasses, perhaps hinting at a more proactive care-seeking behavior enabled by the low cost of access. Third, substitution of visits away from the hospital to a nearby telemedicine center seems likely to be driven by patients who need glasses, in particular, as these patients can substitute a hospital visit and instead get glasses at a telemedicine center closer to home. This is, in turn, likely to reduce the indirect cost of travel and time for these patients, even if the health outcome remains unchanged.

In contrast to the above findings, column (4) of Table 5 shows that the impact telemedicine center openings on the rate of cataract surgeries performed at the hospital is both operationally negligible and statistically insignificant despite the significant positive impact on the visit rate of cataract patients. Camps, on the other hand, show a significant positive impact on the cataract surgery rate despite a smaller impact on the cataract patient visit rate (0.23). Our discussions with the Aravind team and insights from field visits suggest two plausible explanations for this finding. First, patients visiting a camp receive free return transportation to and from the hospital, while those visiting a telemedicine center do not. As a result, patients who visit camps may be slightly poorer than those who visit the telemedicine centers. Similarly, patients visiting the telemedicine centers may be in the early stages of cataract disease progression and hence may not need a surgery immediately. This is consistent with our earlier conjecture about proactive care-seeking among patients in the general clinical group. Determining the specific underlying mechanisms for these effects is beyond the scope of our study design and requires further research.

### 5.5. Patient costs

Here, we investigate the impact of increased use of healthcare services and increased delivery of treatments to patients on their direct and indirect costs. This is important in our study setting because health insurance coverage is very low and most healthcare expenditure is borne by the patients themselves (Pandey et al. 2018). We measure direct cost using the amount billed by Aravind to patients per 1000 persons in treatment locations (termed as "charge rate") and indirect cost using the proxy of average distance travelled per visit.

**Table 6 Monthly Patient Costs and Distance**

| | Charge Rate (₹) | | | Distance (km) |
|---|---|---|---|---|
| | (1) Network | (2) Telemed. Center | (3) Hospital | (4) Network |
| Telemedicine Center [0-10km] | -14.57 | 81.69*** | -96.25 | -11.82*** |
| | (129.49) | (8.43) | (128.08) | (0.80) |
| Observations | 186552 | 186552 | 186552 | 149752 |
| Adjusted $R^2$ | 0.209 | 0.268 | 0.208 | 0.905 |

All regressions include location and time FEs, as well as variables for camps, and controls as given by equation (2). Two-way clustered standard errors (Census Location i, Period t) show in parenthesis.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6 shows the impact of telemedicine centers on the charge rates (direct costs to patients) and that on the distance traveled (indirect costs to patients). Column (1) shows that the introduction of a nearby telemedicine center does not significantly impact the charge rate across the network. The charge rates at telemedicine centers however do show a statistically significant increase (column (2)). Nonetheless, economically this effect is modest, ₹82 $\approx$ \$1.15 per month per 1000 people. There is no statistically significant evidence for any effect on the charge rate of hospital channel. Column

(4) on the other hand shows a decrease of 11.82 kilometers in the average distance travelled by patients to receive care. This translates into a 30% reduction in average distance travelled for census locations within ten kilometers of a telemedicine center. (Note that this is the decrease in average distance travelled conditional on having at least one visit from a census location in a month, which is why the number of observations shown in column (4) is 149,763 instead of 186,552.)

In summary Table 6 shows the rate at which patients incur charges from the Aravind network is not impacted by the introduction of telemedicine centers but that conditional on accessing care, the average indirect costs decrease by approximately 30%. This analysis provides clear evidence of the direct economic benefits of telemedicine centers to patients.

### 5.6. Distance heterogeneity

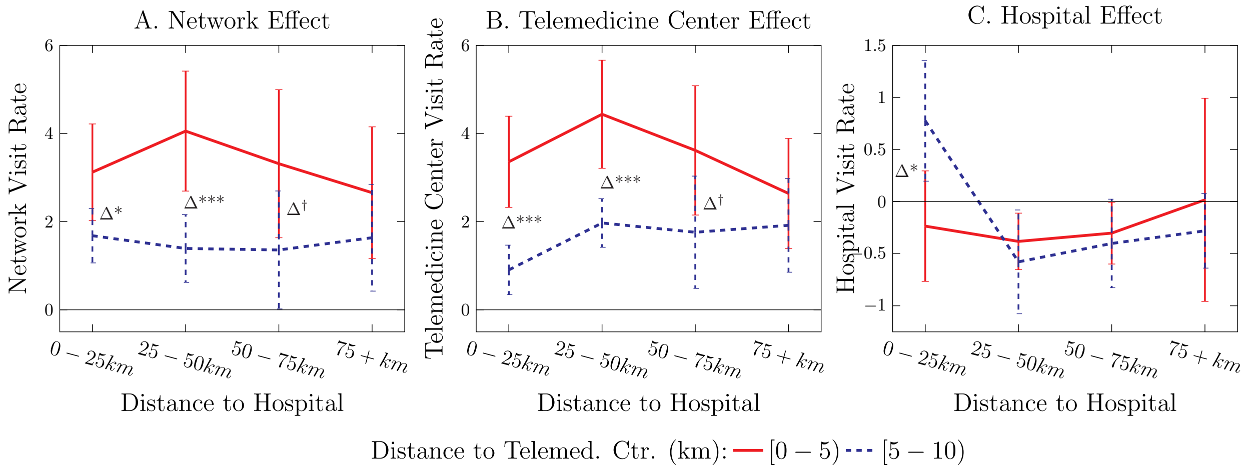
Patients' distance from different channels of care delivery impacts their direct and indirect costs of accessing care, and therefore influences their choice of the channel.[18] However these effects of distance cannot be estimated in the main model as they are absorbed by the location fixed effects. Hence, to further investigate the role of physical distance, we examine how the treatment effect of opening a nearby telemedicine center changes with the relative distance of the hospital and the telemedicine center from the patient's location. One expects that the expanded use of health care services and substitution of hospital visits due to opening of a nearby telemedicine center will be greater for patients living closer to the telemedicine center. However, this differential impact may also be moderated by the patient's distance to the hospital, as those living closer to the hospital would benefit less from substitution, everything else being equal.

To study these heterogeneous effects, we define two categories of treatment locations, first those that are within 5 km and second those that are $5 - 10$ km from a telemedicine center. We then interact indicator variables for each of these categories with those representing the following four groups based on the distance from the hospital: $0 - 25$ km, $25 - 50$ km, $50 - 75$ km, and $> 75$ km. We depict the coefficient estimates of these interactions along with 95% confidence intervals in Figure 4.

Sub-figure A shows the impact of telemedicine centers on the network visit rate. First, this impact is positive and significant for both categories of treatment locations irrespective of their distance from the hospital. Second, as expected, the impact is significantly larger for treatment locations that are closer to the telemedicine center, i.e., $0 - 5$ km except when the distance from the hospital is greater than 75 km. Third, the magnitude of the impact within each category

[18] For instance, descriptive statistics show that hospital visits from patients living 25-50km and more than 50km from the hospital are 41% and 60% fewer, respectively, compared to those living within 25km of the hospital. Details are available in Table 23 in §A.2 of the Online Appendix.

**Figure 4 Heterogeneous effect of telemedicine centers on visit rate by distance.**




*Note, where the effects of telemedicine centers are significantly different in the first 5km compared to the region from 5-10km from a telemedicine center, we have indicated this with a Δ on the figure, where we have indicated significance using:*$^{\dagger}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

of treatment locations does not vary with distance to the hospital as seen from the overlapping confidence intervals.

Sub-figure B shows the impact on the visit rate to the telemedicine centers and reflects most of the trends from Sub-figure A with one exception. For treatment locations that are $5 - 10$ km from the telemedicine center, the impact is smaller if the distance from the hospital is $0 - 25$ km (p=0.006). This finding suggests that patients may be more sensitive to the indirect cost of accessing a nearby telemedicine center if they are close to the hospital, possibly due to significantly higher perceived value of hospital care and relatively lower absolute change in distance to the telemedicine center.

Sub-figure C shows, as expected, that the impact of a telemedicine center on the hospital visit rate from a treatment location varies substantially depending on its distance from the hospital. The impact is negative, denoting substitution, for treatment locations that are more than 25 km from the hospital although statistical significance is lower for larger distances from the hospital. Interestingly, we find a positive and significant impact on the hospital visit rate from treatment locations that are relatively farther from the telemedicine centers ($5 - 10$ km) but relatively closer to the hospital ($0 - 25$ km). Although we cannot not directly measure it, this effect suggests the presence of a marketing effect of telemedicine centers, where patients become aware of Aravind's services due to the presence of a telemedicine center in their community and are willing to incur the indirect cost of traveling to the hospital due to its relative proximity.

In summary, these results bring out two important managerial insights. First, the incremental volume of patients received at the telemedicine centers is very sensitive to small changes in distance from patient communities. Second, the impact of telemedicine centers on patient volumes at the hospital can be negative or positive depending on the distance of the patient community from the hospital. These insights imply that the "optimal" network of telemedicine centers should incorporate distance from patient communities to existing tertiary care hospitals in addition to potential telemedicine center locations.

## 6. Robustness Checks

In this section, we check for the robustness of our results to alternate model specifications and different sub-samples of our data that aim address possible violation of key assumptions underlying our empirical strategy. The estimates for all checks described are provided in §A.1 of the Online Appendix unless otherwise indicated.

### 6.1. Parallel Trends

Identification in DiD models hinges crucially on the assumption that outcome measures in treatment and control groups follow parallel trends. While a pre-treatment trend for the treatment group is never significant, using pre-treatment placebo tests (Bertrand et al. 2004), we find some limited evidence against the parallel trends assumption during pre-treatment periods. Specifically, we find that among the 19 outcome variables this assumption may not apply only for cataract visit rates, cataract treatments and overall charge rates (see §A.5 of the Online Appendix for details of the procedure and Table 25 for the results). A second possible violation of parallel trends can occur post-treatment if the treatment effect spills over into the control group. To test the robustness of the main results to potential violations of the parallel trends assumption, we use both a modified formulation as well as a sub-sample analysis.

The first approach uses an alternate model specification that includes census-location-specific time trends as well as a spillover control variable for census locations that are $10-15$ km away from the nearest telemedicine center.[19] Table 7 in §A.1 shows that almost all of our results continue to hold for this specification; the only exception is that the decrease in the hospital visit rate (Column (3)), is not statistically significant. We also note that the magnitude and significance of the impact on the cataract visit rate and null results for the impact on cataract surgery rate and charge rates (for which parallel the trends assumption was potentially violated), are robust to this change in specification (Columns (9) and (10) of Table 7 in §A.1).

The second approach focuses on testing the robustness to spillover of the treatment effects to the control group by restricting the control group to the sub-set of census locations that are further away. Tables 8 and 9 in §A.1, provide the estimates when the control group is limited to locations more than 15km, and 20km, from a telemedicine center, respectively. All results remain robust

[19] Our results are robust to extending the spillover effects to census locations in the treatment group, i.e., locations that have a telemedicine center within 10 km and another telemedicine center within 10-15 km.

to these exclusions, though we note that when the control group is restricted to locations more than 20km from a telemedicine center, the reduction in the hospital cataract visit rate becomes significant in this reduced sample, which is perhaps due to this subset of locations being further from the hospital.

### 6.2. Endogeneity

Here, we test the robustness of our results to possible endogeneity arising from selection of treatment locations or treatment timing based on unobservable factors that are not captured in our propensity score model. We investigate the possibility of such endogeneity through a set of sub-sample analyses.

**6.2.1. Location** To account for the possibility that treatment and control locations differ on unobservable factors, we restrict our attention to the sub-sample comprised of only treated locations, i.e., census locations within 10km of any telemedicine center in the last period of our observation window. The assumption here is that since all locations are treated, they are less likely to vary on unobserved factors which could have influenced the estimates in §5.

We further restrict estimation to the first 86 time periods to ensure that the control group (i.e., census locations more than 10 km from a telemedicine center) is not empty for any of the periods in the restricted sub-sample. Approximately 20% of observations remain in the control group after this restriction. Further, given that all the locations in this model are eventually treated, we do not use the first-stage propensity score, restrict the sample to common support or apply inverse probability weightings.

Table 10 in §A.1 shows that all of the significant results from the main analysis continue to hold in this case. In addition, we find that the reduction in hospital visit rate for cataract patients is also statistically significant, which may be due to reduced overall variance in this sub-sample compared to the larger set of locations in the dataset.[20]

**6.2.2. Timing** To examine the robustness of our results to potential endogenous timing (e.g., if Aravind prioritized locations with greater potential of impact to open the first few telemedicine centers), we re-estimate our models on three sub-samples of telemedicine centers that opened in the early (periods 1–38), middle (periods 39–76), and late (periods 76-112) phases of our observation window (Jayaraman and Simroth 2015).

Similar to the previous subsection, we work with only the locations in the treatment group, to minimize concerns about endogeneity of location choice. Further, to ensure that the there are

[20] Considering only the eventually treated locations changes the interpretation of the coefficients as they are less likely to generalize to other locations that are dissimilar. Nonetheless, this analysis provides an indirect check which indicates that selection into treatment based on unobservables is not likely to have had a significant impact on our estimates.

adequate control observations for the third subsample (late phase), we add 7,952 observations corresponding to locations that were "treated" by four telemedicine centers that opened after the end of our observation window (May 2015). [21]

The estimates, provided in Tables 12–14 of §A.1, are similar in terms of magnitude and significance across the three subsamples and similar to our main results for the original sample. The main exception is that the reduction in the hospital visit rate (overall and for general patients) is no longer significant, which may be due to smaller sample sizes. Overall these results suggest that endogeneity with regard to the timing of opening of telemedicine centers does not seem to have a significant impact on our main insights.

### 6.3. Competition

Thus far, we have implicitly assumed that an increase in network visit rate due to opening of telemedicine centers indicates improved access to healthcare. However, it is plausible that this increase is merely substitution of visits away from Aravind's competitors and not a true increase in access. To check for this possibility, we collect data on the location and date of opening of facilities operated by Aravind's competitor in our study districts. We identify 48 such facilities, of which 23 had already opened before January 2006 and would be absorbed in the location fixed effects whereas an additional 25 opened during our observation window. We find that 221 out of the 657 locations in the treatment group within common support (33.6%) have no competitors within 20km. Compared to the control group, the treatment group has fewer competitors within 10km (1.00 vs. 1.16) but more competitors between 10-20km (3.52 vs. 2.71). See Figure 7 in §A.4 for a map of these locations.

We modify the first-stage propensity score model to include indicator variables for the presence of at least one competitor in the 0-10km and 10-20km regions as well as a continuous variable for the number of competitors in these regions at the end of the observation window (May 2015), when we also measure the binary dependent variable indicating whether a location is treated or not.[22] Further, we also modify the second-stage DiD specification by including controls for the number of competitor facilities within 0-10km and 10-20km, as well as their interactions with the main treatment indicator variable $TC_{it}$. In this specification, main effect (the coefficient $TC_{it}$ can be interpreted as the average impact of a telemedicine center on locations that do not have a competitor within 20km.

[21] Before proceeding with the analysis of interest, we confirm that our main results are robust to estimation on this subsample (Table 11 in §A.1) with the exception that reduction in the hospital visit rate for cataract patients becomes statistically significant, as also observed in §6.2.1 (Table 10 in §A.1.)

[22] Table 15 in §A.1 shows that the estimates of our original propensity score model are robust to inclusion of competitors. Furthermore, it also shows that the impact of competition on choice of treatment location is mixed; the odds of a location being treated decrease by 72.3% if it has a competitor within 10km but they increase by 14.5% for each additional competitor within 10km.

Table 16 in §A.1 shows that the results for locations that do not have a competitor within 20km are consistent with those in our original specification. This provides further support for the interpretation that telemedicine centers increase access in underserved communities. However, the table also provides mixed evidence for the impact of competition on various outcomes, thereby adding nuance to our main results. For example, each additional competitor within 20km reduces the telemedicine center visit rate (Column 2) but increases the hospital visit rates (Columns 3, 5 and 7).[23]

### 6.4. Additional robustness checks

We test the robustness of our model to any long-term effect of camps by controlling for the number of camps held within 10km of each location in 12 months preceding each period. This variable itself is not consistently significant across all models and estimates of our main model are robust to the inclusion of this variable with one exception; reduction in hospital visit rate for cataract patients becomes statistically significant in the new model. See Table 17 in §A.1 for more details.

We also test the robustness of our results to exclusion of low volume census locations (average of less than two network visits per time period), which reduces the number of observations from 186552 to 136460 and number of observations with zero visits from 19.2% to 5%. Table 18 in §A.1 shows that all statistically significant results from the main analysis continue to hold for this sub-sample. Furthermore, similar to the analysis on sub-sample of treated locations in the first 86 periods, we find that the reduction in the hospital visit rate for cataract patients becomes significant. We note that the robustness of results extends when the threshold (average of two visits per month) used to define low volume locations is varied.

Finally, we confirm that all the statistically significant coefficients in our main results are robust to two different levels of clustering of the standard errors on the geographical dimension, while keeping the time dimension of clustering fixed at the level of a month. Table 19 in §A.1 shows the results for clustering at the sub-district level and Table 20 in §A.1 shows the results for clustering at the level of the closest telemedicine center.

## 7. Discussion

Telemedicine is being increasingly deployed in developing countries across the world with the promise of improving access and outcomes while simultaneously reducing costs. However, the actual impact of telemedicine models in these settings, especially its cross-channel implications, is not well understood. This paper examines the introduction of rural telemedicine centers in Southern

[23] We note that this may be due to collocation of competitors in markets with higher demand, e.g., more urban locations.

India, where patients are seen locally by a mid-level provider who facilitates a tele-consultation with a remote physician.

We find that telemedicine centers increase the overall patient visit rate substantially, in large part due to more new patient visits. However, the magnitude of this increase is larger for patients with simple ailments (e.g., refractive errors) than for those with complex conditions (e.g., cataract). Further, these increased visits translate into increased treatments for simple ailments (e.g., glasses prescription) but not for complex conditions (e.g., cataract surgery). Telemedicine centers also reduce patient visits to the hospital, an effect which is mostly driven by patients with "simple" needs, though we note there is some evidence of reductions in hospital visits among the more "complex" patient populations as well. Finally, there is significant spatial heterogeneity in the impact of opening a telemedicine center depending on the distance of patients from both the telemedicine center and the hospital. Our results are robust to possible endogeneity in the timing and location of opening of telemedicine centers, and presence of competition.

These findings have significant operational implications for healthcare providers. They shed light on the benefits and limitations, as well as the cost effectiveness of implementing a telemedicine center channel of care. For example, given the increases in visits or treatments from the surrounding population, healthcare providers can quantify the appropriate catchment population or the cost at which a telemedicine center is preferred over alternate models to improve patient access (e.g., community health workers, mobile vans). These results also have important implications for network design decisions such as location and capacity of telemedicine centers.

The large scale and integrated nature of the Aravind Eye Care System allows us to conduct rigorous empirical estimation of the cross-channel effects of telemedicine. Similarly, the demonstrated replicability of the operating model within India as well as in other developing countries, e.g., Combi et al. (2016), enhances the generalizability of our findings. Nonetheless, there are certain natural limitations of our study, which could be addressed through further research. First, the specific empirical estimates obtained in our study context are also a function of Aravind's reputation and brand recognition in the region. It is unclear whether telemedicine centers opened by a new entity without these advantages will be able to achieve similar increase in access. Second, ophthalmology is ideally suited for clinically effective use of telemedicine due to availability of several low cost imaging techniques. Our findings may be more applicable to other specialties with similar characteristics (e.g., dermatology, oncology) than to those requiring a thorough physical examination. Third, and final, our results come from a developing country setting and may not be broadly generalizable to developed countries except for pockets of underserved and underinsured rural communities within them.

In developing the first comprehensive evaluation of the cross-channel effects of telemedicine centers, we have focused on metrics related to the use of health care (visit and treatment rates), which are distant determinants of health outcomes. Future work should investigate the more proximate measures of health outcomes, e.g., early diagnosis, reduced post-surgical loss to follow up. Analysis of these effects will, most likely, require prospective collection of longitudinal clinical data, which is beyond the scope of our study. Future studies could also study operational challenges posed due to the decentralized nature of telemedicine center operations (e.g., stock outs, unreliable network connectivity) and their impact on quality of care. Finally, another promising direction for future research is disentangling and quantifying marketing effects of introducing the new channel of care on hospital visits from the cross-channel substitution effects.

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