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Spillover Effects of Mission Activities on Revenues in Nonprofit Health Care: The Case of Aravind Eye Hospitals, India

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Abstract

Nonprofit health care organizations in low- and middle-income countries often pursue a cross-subsidization business model wherein services are offered to poor patients for free through surpluses generated by serving some patients at market prices. This approach allows such organizations to fulfill their mission-oriented and revenue-generation goals. Conventional wisdom holds that mission activities need financial subsidies from revenue-generating activities. The authors examine this dependence in the context of Aravind Eye Hospitals, which delivers eye care services in India. They measure whether the marketing activities (outreach camps) of Aravind that are targeted only to poor patients produce the spillover benefit of attracting paying patients to its hospitals. Using nine years of patient-level historical data, the authors find that camps increase the flow of paying patients. These effects are comparable to the camps acting as advertising for Aravind. Using model estimates, the authors compute the incremental revenue accruing to Aravind from a camp and find that it exceeds the incremental cost of a camp. The findings challenge conventional beliefs about the subsidies required by mission activities.

Keywords

cross-subsidization, developing economies, health care, not-for-profit, spatial effects

Organizations that deliver health care exhibit three main forms of ownership: private for-profit, private nonprofit, and public (or government). For-profit firms are owned by shareholders or investors and usually distribute some proportion of their profits to owners. Nonprofit institutions either do not have owners or are owned by "members," such as religious organizations, communities, or nongovernmental organizations. Nonprofit firms are barred from distributing profits to persons who exercise control over the firm (Hansmann 2000). Their purpose is often to fulfill a stated mission (e.g., to provide health care to the poor, to perform research and teaching) while remaining economically sustainable.

An important feature of the health care delivery sector worldwide is the significant presence of private nonprofit organizations. In the United States, approximately 60% of community hospitals were nonprofit entities in 2015, and the rest were roughly equally divided between private for-profit and government hospitals (American Hospital Association 2017). Sloan (2000, p. 1144) notes that "the for-profit hospital is clearly in the minority numerically in all developed countries." In low- and middle-income countries, there is extensive participation by nonprofit providers as well (Mills 2014).

A sizable body of theoretical work in economics offers models of nonprofit firms' behavior, especially in the health care sector. One theory, in line with the altruistic preferences of owners, asserts that nonprofit hospitals have an intrinsic motivation to serve (e.g., Newhouse 1970). Another theory argues that nonprofit hospitals operate as physicians' cooperatives, with the objective of maximizing the income of doctors on the hospital's medical staff (e.g., Pauly and Redisch 1973). A third theory suggests that nonprofit hospitals exist to overcome the problem of asymmetric information about quality between consumers and hospitals that cannot be controlled by explicit contracts (Easley and O'Hara 1983; Glaeser and Shleifer 2001). Available empirical evidence for the U.S. market does not

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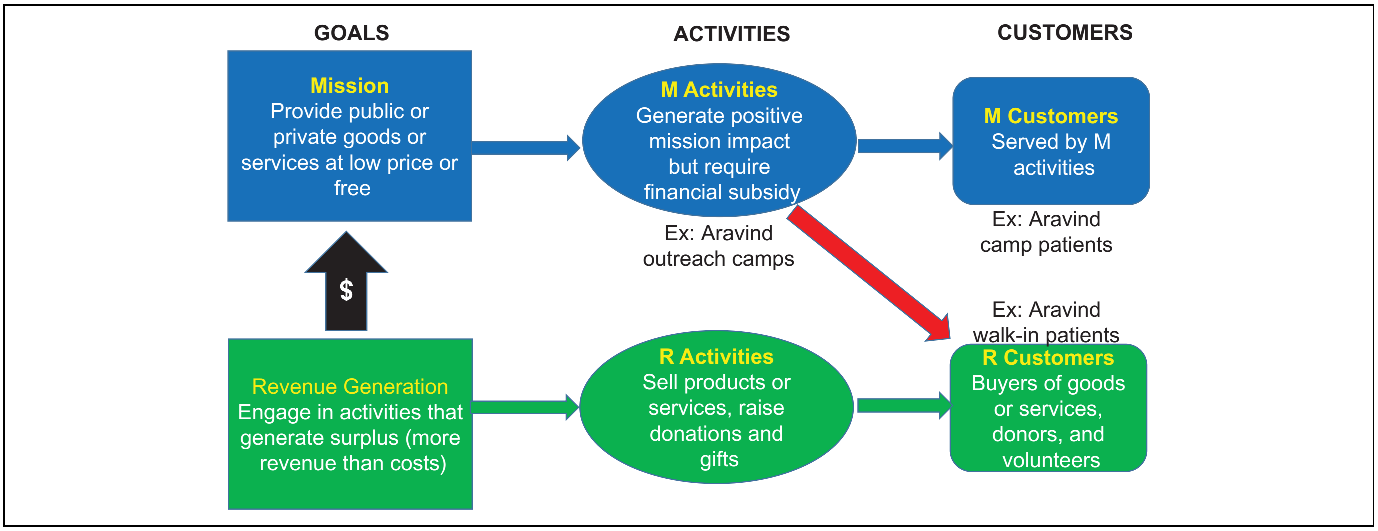

Figure 1. Nonprofit organizations' goals, activities, and customer groups.

support a single theory as dominant, although the physicians' cooperative theory has been found to not be relevant (Malani et al. 2003).

Low- and middle-income countries are characterized by both a large burden of disease and considerable barriers to the delivery of health care, such as poor infrastructure. Moreover, these countries have major gaps in government-provided health services, leading to extensive participation by private providers. However, private for-profit providers' services are not affordable for large sections of the population. Therefore, nonprofit organizations motivated by altruism have come to play an important role in these markets. Herein, we focus on a widely prevalent business model for nonprofit hospitals in low- and middle-income countries. In this model, hospitals offer services to poor patients for free or at very low prices, and they offer services at higher prices to patients who can afford them.[1] The margins from the latter group of patients subsidize health services to poor patients while allowing the hospital to remain financially viable.

This business model, which is based on a price discrimination strategy, has been termed "cross-subsidization." Adapting terminology introduced by Weisbrod (1998), we classify the activities of organizations that pursue cross-subsidization models into two categories: M activities (M standing for "mission"), which serve M customers, and R activities (R standing for revenue), which serve R customers. These are depicted respectively in the upper and lower parts of Figure 1. There are many examples of the use of cross-subsidization to deliver health care to the poor on a large scale.[2] Examples include CARE Hospitals, which provides primary care, cardiology, and other specialty services in India and subsidizes up to 70% of its patients; Narayana Hrudayalaya Hospital, which performs approximately 12% of heart surgeries in India and subsidizes 60% of its patients; and Lumbini Eye Institute, which meets 25% of eye care needs in Nepal and subsidizes 12% of its patients (Bhattacharya et al. 2010; Tung and Bennett 2014). One of the best-known organizations is Aravind Eye Hospitals in India, which practices cross-subsidization as the core of its business model (Rangan 2009) and is the subject of our empirical study.

An important aspect of many nonprofit health care providers that employ the cross-subsidization model is the use of marketing activities that are primarily tailored to poor patients (Bhattacharya et al. 2010; Tung and Bennett 2014). The use of outreach and education efforts targeted specifically to poor patients is necessary because these patients have limited purchasing power, are located in underserved geographical areas, and have low health literacy. Studies have shown that despite the magnitude of need among these populations, only a small percentage seek out health care on their own. Fletcher et al. (1999) concluded, based on a field experiment in South India, that 93.2% of individuals who could have benefited from eye treatment did not pursue any available services. More recently, Olusanya et al. (2016) found that 75% of adults in a rural community in southwestern Nigeria who needed eye care were not utilizing eye care services. As a result, marketing to generate demand is a critical ingredient for improving eye health in the population (see also Bertrand, Mullainathan, and Shafir

[1] In a similar manner, nonprofit hospitals in the United States also provide uncompensated care to poor patients. In addition to the social mission, the literature (e.g., Nicholson et al. 2000) attributes such behavior in part to community service required to maintain tax-exempt status under U.S. Internal Revenue Code section 501(c)(3).

[2] The cross-subsidization model is popular not only in health care but also in nonprofit organizations in general. Oster (1995) provides several examples. Jahani and West (2015) discuss enterprises that focus on base-of-the-pyramid markets using cross-subsidy models and why such organizations may be attractive to impact investors. A chain of four restaurants in Spain aptly called Robin Hood (Minder 2016) serves breakfast and lunch at full price to paying customers and free dinner with "tablecloths, chandeliers, water glasses, and even someone to serve you" to homeless clientele.

[2006], who argue for the need for marketing to aid in decision making among the poor).

At the same time, these health care providers often devote little or no resources to marketing to paying patients, either because of unavailability of funds or because they believe that marketing to paying patients contradicts their social mission.[3] Importantly, these nonprofits commonly face competition in acquiring paying patients from for-profit providers of health care services. Given the unusual focus on marketing to customers who do not pay or pay relatively little, an important strategic question to ask is whether the marketing efforts directed to poor patients have a spillover impact on the demand from paying customers. The occurrence of such spillover effects would constitute evidence of interdependence between the mission and revenue sides of health care organizations using cross-subsidization models, which has so far been overlooked in the literature.

The main focus of our research is to theorize how such spillover effects may occur, to measure and characterize them in the case of Aravind Eye Hospitals (Aravind hereinafter), and to provide insights into the interdependence between the R and M sides of similar organizations. In our empirical study of nine years of historical data related to the traffic of paying patients treated at one major Aravind hospital, we find strong evidence that marketing activities directed to poor patients increase the flow of paying patients. To estimate these effects, we use panel data to exploit the spatial and temporal proximity of patients to the spatial and temporal occurrence of marketing activities (outreach camps). This evidence challenges the assumption that M activities must be subsidized by the R side of nonprofit organizations. This assumption is a fundamental aspect of recent research in operations management related to allocating resources between revenue and mission sides of Aravind-like nonprofit organizations (De Vericourt and Lobo 2009). An organization that disregards the spillover benefit we study is likely to invest suboptimally in M activities. Thus, our article has important implications for the management of nonprofit health care organizations. Next, we present a brief background of Aravind before describing the research objectives and intended contribution of this article.

Aravind Eye Care System

Since its inception in 1976, the Aravind Eye Care System has pursued its mission of "eliminating needless blindness by providing high quality, high volume, compassionate eye care to all." In 2016–2017, Aravind's outpatient visits exceeded 4.0 million (Aravind Eye Care System Activity Report 2016–2017[4]). In that year, Aravind eye surgeons performed over 463,000 surgeries and laser procedures, and 48% of those surgeries were free or deeply subsidized. These statistics make Aravind one of the world's largest and most productive eye care organizations. Much has been written about Aravind's business model (e.g., Rangan 2009) and operational efficiency (e.g., De Vericourt and Lobo 2009). However, to our knowledge, there is little published research on the marketing of Aravind's services.

Aravind was founded in 1976 by Dr. G. Venkataswamy as an 11-bed hospital in Madurai in the southern Indian state of Tamil Nadu to provide care for patients with disabling cataract blindness. Cataracts are the major cause of blindness in developing countries, making up 41.7% of all cases in South Asia in 2010 (Jonas et al. 2014). A cataract forms as the natural lens of the eye clouds over time. Among other factors, poor nutrition and tropical weather are believed to be significant risk factors for cataracts. In most cases, a cataract can be surgically removed, and the eye's natural lens can be replaced by an artificial one known as an Intraocular Lens (IOL). Since its inception in 1976, Aravind has seen dramatic growth in volume and service capabilities.

A central tenet of Aravind's business model is to be financially self-sustaining through earned revenues, with almost no reliance on grants or philanthropy. It has achieved this goal by following the cross-subsidization model. To achieve its mission of serving the under-served, especially the rural poor, Aravind serves a large number of paying patients who can afford to pay market rates. Patients who cannot afford to pay market rates are provided care for free or at heavily subsidized prices. Because of the cross-subsidization model, Aravind has generated surpluses that have funded its engagement and rapid growth in ventures such as manufacturing IOLs.

At Aravind, the core services (e.g., surgery, comprehensive eye examinations) are essentially the same for paying and nonpaying patients in that they are provided by the same team of physicians and surgeons. However, Aravind does provide unique services to paying patients by offering several different surgery techniques and IOL types, as well as accommodation options related to beds, air conditioning, and semiprivate bathrooms. All patients self-select whether they wish to be free or paying patients, and if the latter, they choose one of several price–service bundles. This can be viewed as a form of second-degree price discrimination through versioning.

An important decision that the Aravind founders had to make was where to focus the organization's marketing efforts. Vision impairment is widespread among poor patients who typically lack awareness and understanding of treatment options and do not have the knowledge or financial resources to be treated. Thus, marketing to poor patients, especially in rural markets, was essential for Aravind to fulfill its mission. To reach these patients, Aravind developed an extensive community outreach program that includes eye-screening camps, mobile units, and vision centers. At the same time, more affluent patients have choices in terms of eye care service providers in southern India beyond such community outreach programs (examples of private providers include Vasan Eye Care,

[3] Bertrand, Mullainathan, and Shafir (2006, p. 19) note that nonprofits spend little on marketing in general: "It is noteworthy that whereas the private sector spends great amounts of money and attention on marketing, government and not-for-profit organizations typically do not. The latter appear to be driven by the assumption that their policies and social programs, as well intentioned and worthwhile as they are, will work for themselves."

[4] http://www.aravind.org/content/downloads/AECS%20Report%20201617.pdf.

Sankara Nethralaya, and Hindu Mission Hospital). Furthermore, these patients typically have access to eye care provider information as well as the education and financial resources needed to make a considered choice. This might imply that Aravind should devote some marketing efforts to creating awareness of and preference for Aravind in this segment, which consists of patients who are critical for the financial sustainability of Aravind's business. However, as a matter of principle, Aravind's founders and current management have decided to devote no marketing expenditures directly to attracting this patient group (we have reviewed an audited statement of the organization's operating expenses in 2015 to confirm this).

Outreach Camps

Aravind pioneered the large-scale use of eye screening camps to reach out to the rural poor and bring those who qualified for surgery to the base hospitals. In 2016–2017, over 2,500 outreach camps screened almost 580,000 patients, and the screenings resulted in 92,000 surgeries at Aravind base hospitals. Local community service organizations such as the Lions Club, Rotary Club, community-based nongovernmental organizations, hospitals, and industry associations act as "sponsors" and collaborate to organize the camps. The primary role of the sponsor is to set up a campsite with necessary supporting facilities such as furniture, electricity, and water and to provide food and lodging for Aravind's medical team. The sponsor undertakes publicity for the camp in a radius of about five miles. Promotion outside this radius is not productive because access is a significant challenge for potential camp patients. Promotional activities take the form of distributing handbills and posters; posting notices on publicity boards on street corners, shop billboards, and bus stops; creating loudspeaker announcements; and offering referrals through local doctors, teachers, and village leaders (Velayudhan et al. 2011). Most of the publicity is done two to three days before the camp date. Aravind's specification of an ideal location for a camp is a village or rural town with a population of 10,000 to 20,000, with easy access by surrounding areas. Dates for the camp are chosen to avoid major festivals and elections, as well as local marriages. Eighty percent of camps are held on Saturdays or Sundays.

A well-structured process guides how a patient progresses upon arriving at a camp. The stages include patient registration and eye tests by paramedical staff, followed by an ophthalmologist's examination. If the patient needs eye glasses, they are made available at the campsite for the patients to buy. Patients who are advised to have surgery are transported to the base hospital, either by a hired bus or by public transport, and are accompanied by an Aravind staff member. Because camps are attended predominantly by very poor patients, Aravind provides all services (except glasses) at the camp for free, including transportation to the base hospital, surgery, food, postoperative medications, transportation back home, and follow-up a month later at the campsite.

Patient Segmentation

Aravind's pricing approach leads to segmenting patients into three groups:

1. Free patients: These patients go to an Aravind outreach screening camp and are treated completely for free. Patients who need surgery are transported to an Aravind hospital.
2. Paying patients: These patients walk into an Aravind hospital, choose the "paying section" of the hospital, and are charged for each service based on a menu of product-price options. For example, prices for cataract surgery range from US$100 to US$700.
3. Subsidized patients: These patients walk into an Aravind hospital and choose the "free section" of the hospital. These patients are not charged any consultation fee. Patients admitted for cataract surgery pay approximately US$12, which covers the cost of all surgical consumables, including the IOL, medications used during the hospital stay, and postoperative eye drops for a month.

Related Literature and Contribution

Herein, we develop an econometric model to quantify the spillover effects of outreach camps on the number of new walk-in (i.e., subsidized and paying) patients. By translating this spillover effect into an estimate of incremental revenue and comparing it with the incremental cost of a camp, we quantify the economics of an outreach camp. This knowledge is new to Aravind and will be useful for planning its M activities, as well as for disseminating to hundreds of nonprofit health care organizations that Aravind consults with globally.

Our research contributes to the literature on the economics and management of nonprofit health care organizations in several ways. First, we identify a form of interdependence between R and M sides of such organizations that has previously not been recognized. The classical view is that M activities *always* require a subsidy from R activities. For instance, De Vericourt and Lobo (2009, p. 1114) define M activities as "those that generate positive mission impact but require a financial subsidy." Using this definition, they study the optimal trade-off between consumption and investment of financial resources for the M and R sides and provide guidelines for Aravind-like organizations to determine their resource management strategies depending on the organization's objectives (maximizing social capital) and revenue-generating opportunities. In particular, they provide a threshold policy–based framework for deciding how to allocate available resources to M and R sides of the organization. While the authors capture the contributions of the two sides to the organization's social return, they ignore the impact of the M side on the R side, potentially leading to underallocation of resources to the M side.

Second, we conceptualize and demonstrate empirically that a mechanism for such interdependence involves marketing efforts targeted to M customers that spill over and enhance the demand from R customers. Not accounting for the spillover effects of such marketing efforts would imply undervaluing them, thereby potentially leading to underinvestment. Our empirical application to Aravind's outreach camps demonstrates that the spillover effects allow the camps to easily pay for themselves through the enhanced revenues eventually generated from R customers. This conclusion dramatically changes the prevailing view that camps are primarily cost-enhancing activities.

As discussed previously, a sizable literature in economics proposes models to rationalize *why* nonprofits exist and the conditions under which they successfully compete with for-profit providers. However, there is much less work on *how* nonprofits should be managed. Our analysis indicates that there are complex interactive effects between decisions on the M and R sides in such organizational settings, suggesting an opportunity to develop new, insightful theoretical models.

Another potential contribution of our research is to enhance understanding of alternative business models to serve poor patients. In recent years, there has been a lot of interest in Prahalad and Hart's (2002) advocacy of the "fortune at the bottom of the pyramid," which can be achieved using a low-price, low-margin, high-volume strategy. Others have argued against the practicality of this business model (e.g., Karnani 2007; Simanis 2012). However, the cross-subsidization model as an alternative way to serve poor patients has received much less attention.

In the next section, we discuss a framework to conceptualize spillover effects of outreach camps. Following that, we describe the data and the results of preliminary, model-free analysis. Next, we propose our econometric models and the important issue of potential endogeneity of camp effects. We then provide the empirical results as well as the robustness of our results to key modeling assumptions. Finally, we discuss our findings and conclude.

Spillover Effects of Outreach Camps on Walk-In Patient Decisions

As we have noted, Aravind's outreach camps are organized primarily in villages and rural towns in India. These camps have a direct effect, which is to attract poor patients who need eye care. Our focus is on the indirect or spillover camp effects on the behavior of patients who walk in to an Aravind hospital and pay for service (i.e., either paying or subsidized patients), *not* those who visit a camp and are treated for free. We define this spillover effect to include both the effect of the camp itself (e.g., on passersby who may see the camp), as well as the effect of camp promotion that occurs two to three days before the camp. In our data, we cannot separate the two because the camp and its promotion always co-occur.

Using the literature streams on patient behavior and the effects of marketing activities, we theorize why outreach camps may affect the behavior of walk-in patients. Several types of effects could occur. First, we expect the outreach camps to act as a form of advertising to patients who do not attend the camp.[5] These effects may be both informative and persuasive (Ackerberg 2003). The occurrence of a camp and associated publicity can educate patients about eye disease, inform them about the availability of eye care, or remind them that they need to seek treatment for an existing eye condition. Camps can also make patients aware of Aravind as an eye care service provider, thereby affecting its inclusion in the set of providers that patients consider. In addition, camps can act as a signal of the quality of the Aravind brand, affecting the probability of a patient choosing Aravind as their eye care provider.

Second, we expect camps to generate word-of-mouth influence between patients. An example of such an effect would be that individual A, who sees the camp publicity and/or visits an Aravind camp, tells individual B, who was unaware of Aravind, about her service experience. This leads patient B to walk into an Aravind hospital and seek treatment but pay for service. In our model, which considers the aggregate number of patients, this kind of indirect effect of a camp on walk-in patients (i.e., patient B) is included in the overall camp effect.

A third possible effect of camps is that they permit "free riding" for cataract surgery by patients who, without access to a conveniently located and timed camp, may have chosen to be either subsidized or paying patients. This effect, which we term "cannibalization," may result from patients either delaying or advancing the timing of their care to take advantage of the camp. Cannibalization is a natural result of Aravind's patient self-selection-based pricing strategy. In addition to the attractive (free) price, the proximity of the camp and the availability of free transport to and from the hospital is also an incentive for walk-in patients to go to a camp near them instead of traveling on their own to the base hospital. On the other hand, paying patients can choose from a menu of service options, whereas free and subsidized patients have only one service option available.

A challenge we face is that, given the data, our models will only be able to identify the *net* camp effects on the number of subsidized and paying patients separately. We will be unable to separately estimate the advertising, word-of-mouth, and cannibalization effects of camps. Nevertheless, the estimated net camp effects allow us to fulfill one of our primary research goals: determining the incremental revenue attributable to a camp. In our "Discussion and Conclusions" section, we note future research opportunities that involve breaking down these net effects with more detailed, disaggregate data.

We also consider whether the effects of a camp are larger for subsidized patients or paying patients. Subsidized patients are more similar to camp patients in terms of sociodemographic characteristics than they are to paying patients. As a result, they are more likely to be exposed to publicity and word of mouth about the camp. On the other hand, we expect paying patients to be more

[5] In a very small number of cases, patients who go to a camp are referred to the base hospital and are advised to go there as walk-in patients. This may happen when the patient has uncontrolled blood sugar or if there are other reasons that require the patient to delay surgery. If these patients do register at the base hospital, they invariably do so as subsidized patients and not as paying patients. In our data we do not know the identities of such patients.

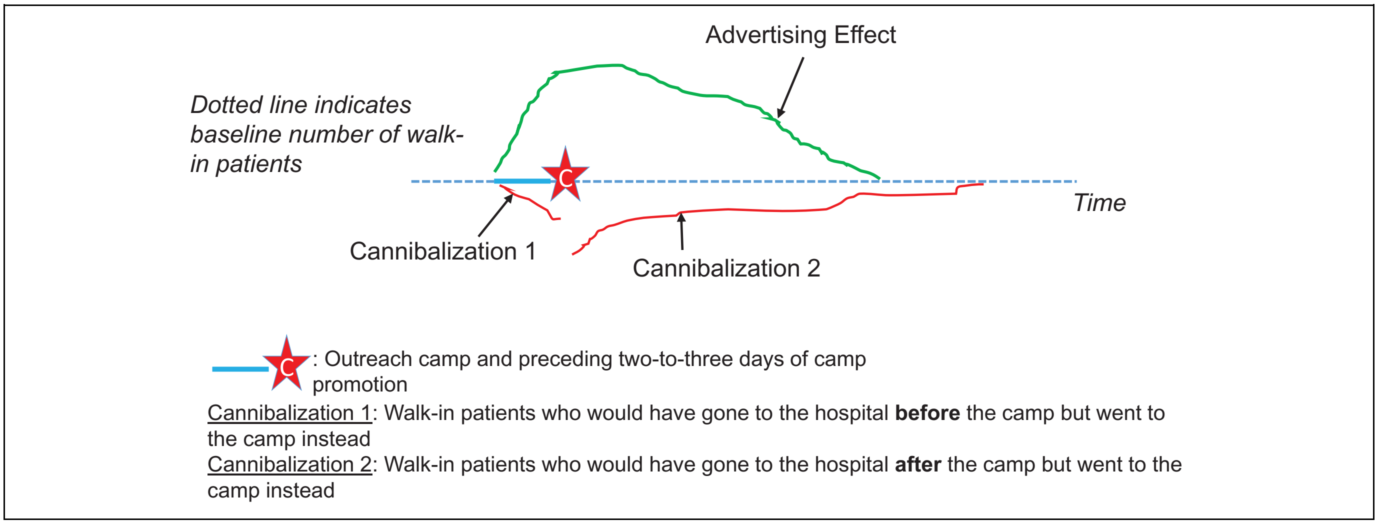

Figure 2. Hypothesized effects of outreach camps on number of walk-in patients.

affluent and thus more mobile, meaning they would be exposed to word of mouth about the camp over a larger geographic area.

Finally, in line with the effects of other forms of marketing communications, we expect camp effects on the number of walk-in patients to carry over into the weeks following the dissemination of precamp publicity and the camp itself. We expect these carryover effects because the timing of most eye care, including cataract surgery, is elective and partly in the patient's control. Moreover, after exposure to the camp or related publicity, the patient's decision to seek eye care may involve consulting with family members, obtaining a referral from a local eye care provider, and making arrangements to travel to the base hospital. At the same time, we expect the advertising effects of camps to decay over time due to forgetting. Consequently, in the model specification, we allow for carryover camp effects but do not impose structure on the shape of the carryover.

Drawing on the previous discussion, in Figure 2 we depict how the advertising and cannibalization effects of camps on the number of walk-in patients are hypothesized to occur. Both advertising and cannibalization effects are expected to be stronger closer to the camp date. Note that the duration and magnitudes of effects are entirely hypothetical in this figure.

Data and Preliminary Analysis

We focused on one of Aravind's newest tertiary care hospitals, Aravind, Pondicherry ("Aravind-P" hereinafter), which started operations in February 2003. We focus on this hospital because reliable data on walk-in patients are only available for recent years; thus, working with a newer hospital allowed us to get patient data from the very inception of a hospital. Aravind-P is located in Pondicherry, a city on the northeast coast of the southern Indian state of Tamil Nadu,[6] and it serves a population of about 21.6 million people in five districts—Tiruvallur, Vellore, Tiruvannamalai, Villupuram, and Cuddalore—as well as the union territory of Pondicherry. There are several government and private for-profit hospitals as well as independent ophthalmologists providing eye care in this region.

Our data consist of approximately 1.4 million new patient visits to Aravind-P from the inception of the hospital in February 2003 until the end of 2014, as well as the dates and locations of outreach camps. Because of concerns about unreliability of patient data in the first three years, we use the data for the nine-year period of 2006 to 2014. For each patient visit, we know whether the patient was a free, subsidized, or paying patient. We also know the patient's home village/town and the date of the patient's visit to Aravind-P. We geo-coded (i.e., obtained latitude and longitude) the village/town of patients' home locations as well as camp locations. We limit our attention to patients who live in Tamil Nadu or Pondicherry. Such patients account for 100% of free and subsidized patients and 99.6% of paying patients.

An important choice we needed to make involved the level of cross-sectional aggregation of the data for modeling. The most disaggregate geo-code information we have for patients is the village/town in which a patient lives, and we term this a patient-market, or market, hereinafter. Consequently, we aggregate the data to the patient-market-week level to obtain the number of weekly visits by new paying and subsidized patients during the period 2006–2014. In addition, we observe all 2,496 camps that were held during this period, and we know the location and week in which each camp was held.[7] We

6. Pondicherry is a city within the Union Territory of Pondicherry. A Union Territory (equivalent to a federal district in the United States) is administered by the federal government and is not part of any state. In 2006, Pondicherry was officially renamed Puducherry.

7. The definition of a week is important. Eighty percent of camps occur on the weekend, and publicity for the camp is performed two to three days before the camp. We wish to capture the joint impact of the camp's occurence and its publicity. Consequently, we define a week as the seven days starting on a Monday. This allows the camp event and the publicity preceding it to occur within a single week for most camps.

Table 1. Descriptive Statistics of the Data 2006–2014.

Variable	Unit	Mean	SD	Min	Max	Total
Number of subsidized patients	Per market-week (541 markets, 470 weeks)	.92	5.57	0	132	234,981
Number of paying patients	Per market-week (82 markets, 470 weeks)	2.11	15.04	0	477	775,226
Number of camps	Per year	277	—	245	300	2,496

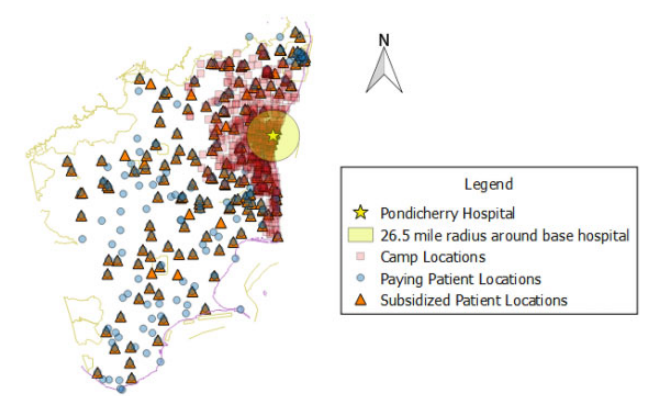

Figure 3. Map of Tamil Nadu showing Aravind-Pondicherry Hospital, camps, and walk-in patient locations in 2014.

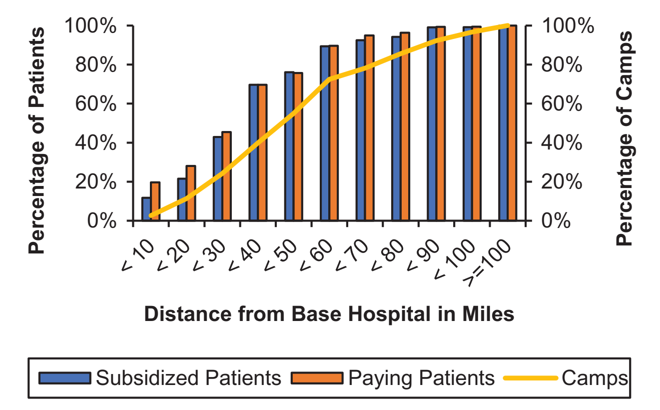

Figure 4. Distribution of walk-in patients and camps by distance from Aravind-Pondicherry Hospital in 2014.

structure the data as two balanced panels of market-weeks, separating subsidized and paying patients. For subsidized patients, we retain the set of 541 markets that had at least one subsidized patient during the period 2006–2014, resulting in 254,270 observations (541 markets × 470 weeks). For paying patients, we retain the set of 782 markets that had at least one paying patient in the period 2006–2014, resulting in 367,540 observations (782 markets × 470 weeks). In Table 1, we show descriptive statistics of the data. On average, there are approximately one subsidized patient and two paying patients per market-week and 300 camps per year.

As we have noted, walk-in patients, both paying and subsidized, travel on their own to Aravind-P. In Figure 3, we show for the year 2014 the locations of patients relative to the base hospital on a map of the Indian state of Tamil Nadu, as well as the locations of 298 camps that year. As expected, there is a heavy concentration of walk-in patients and camps close to the hospital. In Figure 4, we show for 2014 the cumulative distribution of the number of paying and subsidized patients and camps, in terms of distance from the base hospital. Almost 90% of walk-in customers live within 60 miles of the base hospital. Furthermore, in our data there are very few walk-in patients who live more than 100 miles from the hospital. We also note that there are very few camps held within 10 miles of the hospital or further than 90 miles from the hospital. The reasons for this are that patients who are close to the hospital can access it relatively easily; thus, camps are not needed, and patients who are very far from the hospital are difficult to serve through camps because of the travel time required for patients (because they are transported from the camps to the hospital for surgery) and for Aravind-P personnel who staff the camps.

To obtain an initial understanding of the key phenomenon we are trying to measure, which is the effect of camps on the number of walk-in patients, we conduct a preliminary, model-free analysis. The analysis is conducted separately for each of the nine years in the data, as well as for paying and subsidized patients. For each type of patient, we consider only those patient-markets that had at least one patient of that kind in the nine-year period. In each year, we consider only “camp-markets,” defined as patient-markets that had at least one camp within a five-mile radius, and we disregard the other patient-markets. For each camp-market, we divide the weeks into weeks that had a camp in the immediately preceding week (we call these “camp-weeks”), and weeks that did not have a camp in the immediately preceding week (we call these “non-camp-weeks”). We compute the average number of walk-in patients, separately by paying and subsidized patients, in the two sets of weeks. In Table 2, we show the ratio of the average number of walk-in patients in a camp-week divided by the average number of walk-in patients in a non-camp-week, separately for paying and subsidized patients.

This ratio, which we term a “camp multiplier,” ranges between 1.70 and 4.05 for subsidized patients and between 1.04 and 1.19 for paying patients. Deviations of the multiplier from 1 constitute evidence of camp effects, and we see strong evidence of deviations in Table 2. We note that the multipliers are larger than 1 in each of the nine years, and the multipliers for subsidized patients are always larger than the multipliers for paying patients. Given the limitations of model-free analysis, we have limited our attention to camp effects that occur within one week of a camp and within a five-mile radius. Furthermore, we have not controlled for differences between

Table 2. Model Free Evidence of Camp Effects on Number of Walk-In Patients.

Year	Subsidized Patients		Paying Patients	
	Camp Multiplier	Number of Camp Weeks	Camp Multiplier	Number of Camp Weeks
2006	2.17	268	1.17	387
2007	1.98	267	1.12	394
2008	2.48	255	1.19	383
2009	1.82	237	1.10	343
2010	4.05	240	1.13	335
2011	2.60	258	1.15	372
2012	2.35	257	1.06	368
2013	1.87	259	1.08	353
2014	1.70	244	1.04	338

markets, weekly differences, or spatial interdependence between markets. These factors will be explicitly included in the forthcoming model to obtain valid estimates of camp effects.

In interpreting the forthcoming results of model-based camp effects, it is important to bear in mind that camps are not expected to be the primary drivers of subsidized and paying patient traffic in our data. Almost 90% of the variance in both the number of subsidized patients and the number of paying patients can be explained by market fixed effects. Moreover, most walk-in patients do not live close to camp locations: only 12.9%, 23.0%, and 40.9% of subsidized patients live within 5, 10, and 15 miles, respectively, of any camp in our data's nine-year period. The analogous numbers for paying patients are 10.0%, 19.3%, and 37.1%. The reason for this is that camp locations are chosen to allow for easy access to patients who will visit the camps, not to be close to walk-in patients. This point is discussed in detail in the section on potential camp endogeneity, as well as in Web Appendix A.

Model

In line with the previous discussion, our interest is in analyzing the number of new walk-in patients coming to Aravind-P from each patient-market (or "market") in each week. Our primary model is a spatial panel-data model (Lee and Yu 2010) specified separately for y_{mt}^{Pay} and y_{mt}^{Sub}, the number of new paying and subsidized patients, respectively, from market m in week t. Data are observed for M^{Sub} and M^{Pay} markets for subsidized and paying patients respectively, and for T weeks each. The key goal of each model specified subsequently is to use the spatial and temporal variability in the number of walk-in patients to estimate the effects of outreach camps while controlling for differences between markets, years, and weeks.

Because Aravind's walk-in patients are spatially dispersed, it is natural to consider spatial dependence in the number of walk-in patients from different markets. Reasons for spatial dependence to occur include unobserved common variables in proximate markets (e.g., the availability of a competing cataract surgery provider), markets influencing one another as a result of word-of-mouth communication between patients, or measurement error that is correlated through space. We do not have specific theoretically derived expectations regarding the spatial dependence effects; however, we recognize that it is necessary to control for spatial dependence in the model.

Spatial dependence can be incorporated in a spatial panel data model in two primary ways (Elhorst 2009): (1) by including a spatially lagged dependent variable and (2) by including a spatial autocorrelation process in the error term. Following Lee and Yu (2010), we incorporate both features in our model along with fixed effects for markets. This results in a spatial autoregressive (SAR) panel model with SAR disturbances and fixed effects. Bradlow et al. (2005) review the extant marketing literature that employs spatial econometric models. To our knowledge, a model that incorporates both spatial autoregression and spatial autocorrelation in panel data has not been applied to date in the marketing literature. Our model for subsidized patients is as follows:

$$\begin{aligned} y_{mt}^{Sub} &= \lambda^{Sub}\sum_{n=1}^{M^{Sub}} w_{mn}^{Sub} y_{nt}^{Sub} + \omega_m^{Sub} + \mu_{year}^{Sub} + \theta_{week}^{Sub} \\ &\quad + \text{Camp\_Effect}_{mt}^{Sub} + \varepsilon_{mt}^{Sub}, \\ \text{where } \varepsilon_{mt}^{Sub} &= \rho^{Sub}\sum_{n=1}^{M^{Sub}} w_{mn}^{Sub}\varepsilon_{nt}^{Sub} + \upsilon_{mt}^{Sub} \quad \text{and} \quad \upsilon_{mt}^{Sub} \sim N(0, \sigma_{\varepsilon^{Sub}}^2). \end{aligned} \tag{1}$$

The spatial autocorrelation parameters λ^{Sub} and ρ^{Sub} capture spatial dependence between markets, and setting them to zero reduces this model to a linear panel data model. The model for paying patients is specified analogously as follows:

$$\begin{aligned} y_{mt}^{Pay} &= \lambda^{Pay}\sum_{n=1}^{M^{Pay}} w_{mn}^{Pay} y_{nt}^{Pay} + \omega_m^{Pay} + \mu_{year}^{Pay} + \theta_{week}^{Pay} \\ &\quad + \text{Camp\_Effect}_{mt}^{Pay} + \varepsilon_{mt}^{Pay}, \\ \text{where } \varepsilon_{mt}^{Pay} &= \rho^{Pay}\sum_{n=1}^{M^{Pay}} w_{mn}^{Pay}\varepsilon_{nt}^{Pay} + \upsilon_{mt}^{Pay} \quad \text{and} \quad \upsilon_{mt}^{Pay} \sim N(0, \sigma_{\varepsilon^{Pay}}^2). \end{aligned} \tag{2}$$

We next discuss the model specification for subsidized patients shown in Equation 1. Analogous discussion applies to the model for paying patients shown in Equation 2. The first term on the right side of the model in Equation 1, $\lambda^{Sub}\sum_{n=1}^{M^{Sub}} w_{mn}^{Sub} y_{nt}^{Sub}$, captures spatial auto regression by allowing the number of walk-in patients from market m to depend on the number of walk-in patients in other markets. w_{mn}^{Sub} is an exogenously specified nonnegative scalar representing a spatial weight for the pair of markets (m, n), and it is intended to capture proximity between the markets. We eliminate dependence of a market on itself by setting $w_{mm}^{Sub} = 0$. The spatial weights w_{mn}^{Sub} can be thought of as elements of a $M^{Sub} \times M^{Sub}$

spatial weight matrix $\mathbf{W}^{Sub}$ that has zeros on the diagonal. It is common practice to normalize the spatial weight matrix. Kelejian and Prucha (2010) point out that unnormalized spatial weight matrices typically lead to $(I_n - \lambda \mathbf{W}_n)$ being singular for some values of λ in applications. We use spectral normalization (Drukker et al. 2013) in our empirical analysis; however, robustness tests of selected models indicate that results vary little from this choice.[8]

Different definitions of the spatial weights have been considered in the literature. In this research, we consider a contiguity-based weighting matrix $\mathbf{W}^{\mathbf{Sub},k}_{\mathbf{Cont}}$, where $w^{Sub,k}_{mn} = 1$ if $dist_{mn} \leq k$ miles, and 0 otherwise, where $dist_{mn}$ is the Euclidean distance between markets m and n. In the empirical application, we consider different values of the threshold distance k and select the value based on model fit. For robustness, we also consider a spatial weight matrix $\mathbf{W}^{\mathbf{Sub}}_{\mathbf{Exp}}$ that is based on inverse-exponential distance, where $w^{Sub}_{mn} = \exp(-dist_{mn})$. In contrast with the contiguity-based weights, this measure places positive weight on all markets, not just those within the defined distance threshold; however, the weights decline exponentially with distance.

Next, we discuss each element on the right side of the model. Again, analogous discussion applies to the model for paying patients.

$Camp\_Effect^{Sub}_{mt}$

$Camp\_Effect^{Sub}_{mt}$ term captures the effect of outreach camps on the number of subsidized patients who walk into Aravind-P from market m in week t. An outreach camp potentially affects all markets that are no further than z miles from the camp, which we define as the "area of influence" (AOI) of the camp. The smallest AOI we consider is the five-mile radius (i.e., z = 5 miles) in which camp publicity is performed by camp sponsors. A camp's influence can extend beyond five miles because of word-of-mouth transmission and because walk-in patients may be exposed to a camp when they commute or travel.

In addition, we allow for temporal carryover in the camp effects using a finite distributed lag model. Because the camp effect we model is the net of advertising, word of mouth, and cannibalization effects, we are unable to predict its magnitude or sign. Consequently, we allow for complete flexibility and do not impose any structure on the temporal carryover effects. In addition to the week in which the camp is held and pre-camp publicity is done, we include q weeks of separate carryover effects and determine q using a model selection approach that will be discussed subsequently. To operationalize the camp effect, we define C_t to be the set of all camp locations in week t, and $w_{Camp} cm^z = 1$ if $dist_{cm} \leq z$ miles and 0 otherwise, where $dist_{cm}$ is the Euclidean distance between camp c and market m. Defining $Camp_{c,t}$ as 1 if a camp was held in location c in week t, 0 otherwise, our specification of $Camp\_Effect^{Sub}_{mt}$ is as follows:

$$Camp\_Effect^{Sub}_{mt} = \sum_{s=0}^{q} \beta_s \sum_{c \in C_{t-s}} w\_Camp^{z}_{cm} \times Camp_{c,t-s}. \tag{3}$$

β_0 is the contemporaneous camp effect, and β_1 through β_q are the lagged camp effects. The second summation on the right side is a count of the number of camps in week t that fall within a circle with radius z miles, centered at market m.

Market, year, and week fixed effects. ω^{Sub}_m is a fixed effect for market m, m = 1, 2, ..., M^{Sub}. We include these fixed effects to control for a large number of time-invariant unobserved differences between markets that may influence the number of walk-in patients. Relevant market characteristics include socioeconomic factors such as population size and income, industrial development, and work situations and lifestyles in the region. In addition, the fixed effects control for distance to Aravind-P hospital. We opt to use fixed effects instead of random effects because, as discussed previously, the population of patient markets has been sampled exhaustively (Nerlove and Balestra 1996). Because nine years is a long period of time, we allow for yearly fixed effects μ^{Sub}_{year}. These accommodate factors such as trends in cataract-related blindness and treatments, trends in awareness of the disease and of its treatments, changes in competition, changes in Aravind's infrastructure and resources, and changes in sociodemographic characteristics of patients. Finally, θ^{Sub}_t is a dummy variable for week t, t = 1, 2, ..., 52. These weekly fixed effects control for events (unobserved in the data) that recur each year, such as holidays, festivals, elections, and seasons, and that influence the weekly number of walk-in patients. These effects are pooled across years.

Model estimation. We use a quasi-maximum likelihood approach proposed in Lee and Yu (2010). In this approach, a transformation is used to eliminate the market fixed effects ω^{Sub}_m and ω^{Pay}_m. This leads to a conditional maximum likelihood estimator. The parameters to be estimated in each model are as follows: eight-year fixed effects for nine years, 52 weekly fixed effects for 53 weeks, one spatial autoregression parameter, one spatial autocorrelation parameter, and (q + 1) camp effects.

Potential camp endogeneity. An important econometric issue is potential camp endogeneity. Unbiased estimation of the camp effects requires strict camp exogeneity. In other words, the assignment of camps in space and time should be unrelated to outcomes of y^{Pay}_{mt} and y^{Sub}_{mt}. One reason why there might be camp endogeneity is the fact that unobserved factors may affect both the number of walk-in patients from a particular market and week, as well as Aravind's decision to hold an outreach camp in that market and week. These factors could

8. In row normalization, each element of a row is divided by the row sum. In minmax normalization, each element of the matrix is divided by the minimum of the largest row sum and column sum of the matrix. In spectral normalization, each element is divided by the modulus of the largest eigenvalue of the matrix. Kelejian and Prucha (2010) note that row normalization is most commonly used but may lead to model misspecification.

be market-specific (e.g., larger markets receive more camps and generate more walk-in patients), year-specific (e.g., as Aravind-P grew, it held more camps and attracted more walk-in patients), or week-specific (e.g., in a major holiday week, camps are not held and fewer walk-in patients go to the hospital). The market-, year-, and week-specific fixed effects in the model should control for these unobserved factors.

A second situation that might create camp endogeneity is if Aravind managers plan the camps' location and timing strategically in anticipation of walk-in patient demand. This could be to either boost walk-in patient demand because they know about camps' advertising effect or manage the total demand (i.e., walk-ins plus camp patients) relative to available hospital capacity. We rule out the advertising explanation based on interviews with Aravind managers who assured us that the organization has always used outreach activities strictly to fulfill its mission and not to generate revenue.

Regarding the capacity explanation, we offer four arguments as to why this is not likely to be the case. First, we interviewed Aravind management to learn about the camp planning process in detail. The process begins with an annual meeting of hospital general managers at the start of the year in which the managers determine a target number of camps for the upcoming year for each hospital. Each hospital then allocates their assigned number of camps to different markets and schedules the camps for specific weeks of the year. Hospitals adhere to this plan barring exceptional circumstances. Moreover, because planning a camp takes several months of effort by both Aravind and the sponsor, it is not possible to use camps to accommodate short-term capacity concerns at the base hospital. Second, a crucial determinant of camps' location and timing is sponsor availability. Because sponsors are entities external to Aravind, their availability is outside Aravind's control. Third, a capacity-planning-based explanation would imply a negative relationship between camps and the number of walk-in patients. That is, when Aravind anticipates a high number of walk-in patients, it should be less likely to organize camps. However, as we discuss subsequently in our "Results" section, we consistently find a positive relationship. Fourth, we also estimate models with a "placebo" effect, which is the effect of a camp on the number of walk-in patients in the week before the camp. This is a placebo effect because we expect to find this effect to be zero if camps act as hypothesized, namely, that they affect the number of walk-in patients during the camp week, as well as future walk-in patient traffic. We find this placebo effect to be statistically insignificant in all models for both subsidized and paying patients, which contrasts with the significant positive effects on the weeks following a camp.[9]

[9] One approach to account for possible camp endogeneity is to use instrumental variables. However, we did not have access to data on variables that could be theoretically justified as reasonable instruments, namely, variables that are correlated with walk-in patient traffic at the market-week level and are uncorrelated with the occurrence of camps.

Results

We begin the discussion in this section with model selection, followed by interpretations of estimated camp effects in selected models. We conclude with model validation and robustness of results.

Model Selection

For each of the models shown in Equations 1 and 2, our goal is to determine the best-fitting model by selecting z, the radius of the AOI of a camp, and q, the number of lag weeks of camp effects. To do so, we proceed as follows: We initially fix k, the threshold distance in the contiguity-based spatial weight matrices $\mathbf{W}_{\mathbf{Cont}}^{\mathbf{Sub},k}$ and $\mathbf{W}_{\mathbf{Cont}}^{\mathrm{Pay},k}$, at five miles and subsequently test robustness of our results to this choice. Starting with the smallest value of z being five miles, we estimate models with successively increasing values of q. A model with q weeks of lagged camp effects is nested in a model with q + 1 weeks and can be compared using a likelihood ratio test. We stop adding lag weeks when the likelihood ratio test fails to reject the null. We then move on to the next higher value of z (e.g., 10 miles) and pick the best-fitting number of lag weeks. If the likelihood value of the selected model for z = 10 miles dominates the likelihood value of the selected model for z = 5 miles, we use the Vuong test (Vuong 1989) to test the null hypothesis that the better-fitting model is statistically superior. The Vuong test is appropriate because models with different values of z are nonnested but have the same dependent variable. We find that exploration of values of $z \in \{5, 10, 15, 20\}$ miles and $q \in \{0, 1, 2, 3, 4, 5, 6, 7\}$ weeks was adequate to arrive at the best-fitting models for both subsidized and paying patients.

In Table 3, we show fit statistics for a baseline model (without camp effects) and for the selected model. The selected model for subsidized patients has spatial dependence, a camp AOI of five miles, and three weeks of camp effects. The selected model for paying patients has spatial dependence, camp AOI of ten miles, and five weeks of camp effects.

Interpretation of Estimated Camp Effects

Tables 4 and 5 show the parameter estimates and standard errors for the selected models for subsidized and paying patient models, respectively. Note that the effects shown are the total effects, including both the direct effects and the indirect effects due to the spatial interdependence between markets (in Web Appendix B, we describe how these effects are computed). Our most important finding is that camps have significant, positive effects on the number of both subsidized and paying walk-in patients. To characterize the timing of effects, we find that the largest camp impact on the number of subsidized patients occurs in the week after the camp, and a small but statistically significant positive impact continues to occur two weeks after the camp. For paying patients, a positive camp impact occurs during the camp week and persists for four subsequent weeks. As in the case of subsidized patients, the largest impact for

Table 3. Selected Models and Fit Statistics.

Model	Market Fixed Effects[a]	Year Fixed Effects	Week Fixed Effects	Camp Effects	Camp AOI	Log-Likelihood
Subsidized Patients						
Baseline	541	8	52	0	5 miles	−513,510.09
Selected	541	8	52	3	5 miles	−512,774.66
Paying Patients						
Baseline	782	8	52	0	10 miles	−1,047,762.34
Selected	782	8	52	5	10 miles	−1,047,681.43

[a]Market fixed effects are eliminated from the models by transformation and thus not estimated.

Table 4. Parameter Estimates and Standard Errors for Selected SAR Fixed-Effects Panel Model for Number of Subsidized Patients.

Parameter	Estimate	SE	*p*-Value
Camp Week	31.976	17.580	.069
Camp Week + 1	679.181	17.629	.000
Camp Week + 2	63.780	17.616	.000
Year 2007	−.117	.014	.000
Year 2008	−.040	.014	.004
Year 2009	.033	.014	.018
Year 2010	.112	.014	.000
Year 2011	.170	.014	.000
Year 2012	.194	.014	.000
Year 2013	.226	.014	.000
Year 2014	.273	.014	.000
λ^{Sub}	−2.899	.031	.000
ρ^{Sub}	1.150	.004	.000
Weekly fixed effects (not shown)			
Market fixed effects (not shown)			

Notes: Each parameter estimate is the total impact, including direct and indirect effects, due to spatial dependence (see Web Appendix B for the formulae). Camp effects have been scaled by multiplying by 1,000 to permit precise reporting with three decimal points. We obtain standard errors of original model parameter estimates using the inverse of the negative Hessian, after which we use the delta method to compute the standard error of the total impact.

Table 5. Parameter Estimates and Standard Errors for Selected SAR Fixed-Effects Panel Model for Number of Paying Patients.

Parameter	Estimate	SE	*p*-Value
Camp Week	135.782	20.622	.000
Camp Week + 1	184.737	20.607	.000
Camp Week + 2	121.394	20.634	.000
Camp Week + 3	106.438	20.636	.000
Camp Week + 4	73.081	20.667	.000
Year 2007	.067	.025	.008
Year 2008	.175	.025	.000
Year 2009	.186	.025	.000
Year 2010	.244	.025	.000
Year 2011	.433	.025	.000
Year 2012	.505	.025	.000
Year 2013	.696	.025	.000
Year 2014	.904	.025	.000
λ^{Pay}	−3.573	.031	.000
ρ^{Pay}	1.119	.004	.000
Weekly fixed effects (not shown)			
Market fixed effects (not shown)			

Notes: Each parameter estimate is the total impact, including direct and indirect effects, due to spatial dependence (see Web Appendix B for the formulae). Camp effects have been scaled by multiplying by 1,000 to permit precise reporting with three decimal points. We obtain standard errors of original model parameter estimates using the inverse of the negative Hessian, after which we use the delta method to compute the standard error of the total impact.

paying patients occurs in the week after the camp; however, the increase is not as steep as it is for subsidized patients. Notably, the wider area of camp influence on paying patients relative to subsidized patients (ten miles vs. five miles) is consistent with the greater financial resources of this group, which is likely also correlated with greater mobility. In other words, because they are more mobile, paying patients are more likely to see a camp further away from their home or hear about it through word of mouth. Overall, these results are consistent with the idea that camps act as advertising that motivates patients to travel to the Aravind base hospital to seek eye care.

Next, we discuss the magnitude of the camp effects. The three included camp effects in the selected model for subsidized patients are jointly significant relative to the baseline model (see Table 3). Therefore, an outreach camp that occurs within five miles of a market is predicted to increase the number of subsidized patients from that market in a week by .77 patients on average (95% confidence interval [CI] = [.71, .84]), which is computed as (32.0 + 679.2 + 63.8)/1,000, where 1,000 is the scaling factor used in reporting results in Table 4. The analogous number of incremental paying patients is .62 (95% CI = [.48, .76]) computed by summing the five camp effects in Table 5 and dividing by 1,000. To calculate the size of these increments in substantive terms, we compute the incremental number of patients as a percentage of the mean number of subsidized and paying patients per market week in our data (see Table 1). This calculation yields 84.2% (95% CI = [76.9%, 91.5%]) for subsidized patients and 29.5% (95% CI = [22.8%, 36.1%]) for paying patients. Thus, at the level of a market week, the increment in walk-in traffic induced by the occurrence of a camp is substantially large. In Figure 5, we show the percentage increase by week relative to the weekly mean for subsidized patients and paying patients.

We conjecture the following reasons for why camp effects are larger on subsidized patients than on paying patients: (1) paying patients possibly have a preexisting higher awareness of Aravind because of their greater affluence, which

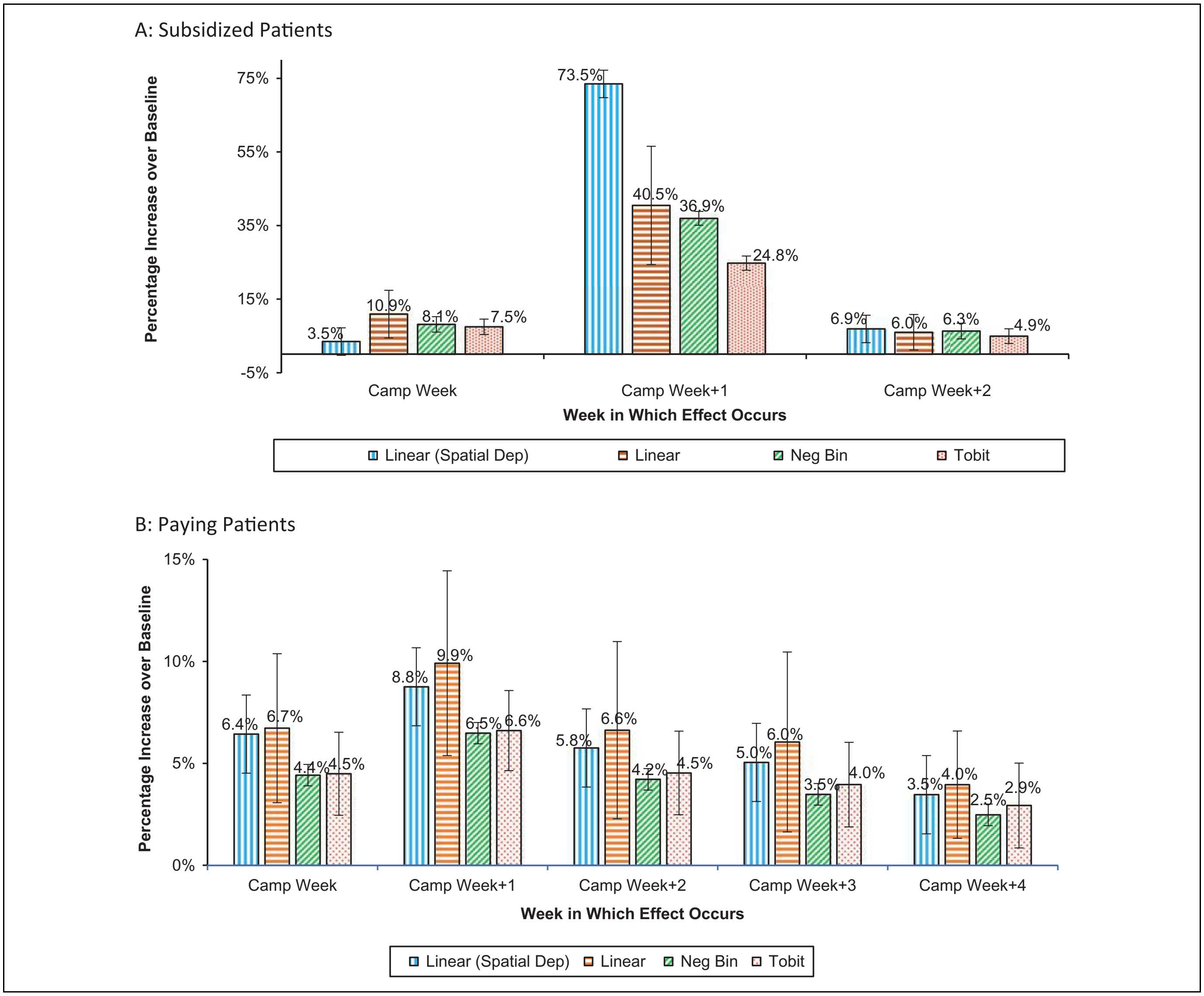

Figure 5. Estimated effect of camps on number of walk-in patients: model comparisons.
Notes: Error bars show 95% CIs.

implies there is less opportunity for camps to influence their behavior, and (2) there is a greater similarity between subsidized patients and camp patients in terms of demographics and socioeconomic characteristics such as income, which implies that subsidized patients would be more likely to be exposed to camp publicity.

Another pertinent issue is *how many* patient-markets a camp influences. We compute the average number of markets that lie in the camp's AOI, estimated to be within radii of five miles and ten miles for subsidized and paying patients, respectively. We find that, on average, 4.3 subsidized patient markets and 15.6 paying patient-markets lie in each camp's AOI. Applying this factor to the incremental number of patients per market-week reported previously, we get the total camp impact to be on average averages 3.3 (95% CI = [3.0, 3.6]) for new subsidized patients and 9.7 (95% CI = [7.5, 11.9]) for new paying patients.

Economics of an Outreach Camp

As noted, the role of camps is to promote the social mission of Aravind, which is to provide free eye care to indigent patients and not to act as revenue-generating advertising. However, because our analysis demonstrates that camps *do* act as advertising, we compute the incremental revenue generated by a camp and compare it with the cost of an outreach camp. We had access to the distribution of payments made by walk-in patients to Aravind-P hospital in 2014. Analysis of these data shows that the average revenue realized by Aravind is approximately US$14 per subsidized patient and US$230 per paying patient (see Table 6 for details). Using the number of incremental new patients reported previously, we estimate the average incremental revenue per camp to be $2,273 (95% CI = [$1,763, $2,785]).

Table 6. Economics of an Aravind Outreach Camp.

A: Costs of an Average Camp

			Camp Size and Number of Outpatients Served		
			Small	Medium	Large
		Daily Cost (INR) (Assumption:	150–200	400–600	700– 1,000
Staff Needed (Capacity to Serve)[a]	Monthly Salary (INR)[b]	25 Working Days/Month)	Staff Needed		
Ophthalmologist (150)	80,000	3,200	1	3	5
Ophthalmic technician (50)	25,000	1,000	3	10	16
Optometrist (60)	25,000	1,000	3	8	14
Optician (40)	25,000	1,000	4	12	20
Counselor (50)	25,000	1,000	3	10	16
		Aravind's cost: Staffing (INR)	16,200	49,600	82,000
		Sponsor's cost (INR)[c]	14,200	22,150	42,050
		Distribution of camps[d]	.59	.39	.02
		Aravind's cost/camp (INR)		30,542	
		Sponsor's cost/camp (INR)		17,858	
		Total cost/camp		INR 48,400 or US$710	

B: Estimated Revenue per Walk-in Patient in 2014[e] (INR)

	Mean	Minimum	Maximum
Subsidized Patient	952	57	8,900
Paying Patient	15,726	30	164,280

[a]Aravind provided the data on camp staffing needs.
[b]The authors estimated the salaries of medical professionals on the basis of discussions with a nonprofit health care provider in India.
[c]Aravind estimated sponsor costs.
[d]The authors estimated these numbers using Aravind-P data for 2013–2014.
[e]The authors estimated these numbers using Aravind data for 2014.
Notes: INR = Indian rupees. 1 USD = INR 68.17.

In Table 6, we also provide an estimate of the total costs of a camp. These costs are divided into (1) costs paid by the sponsor, which include camp publicity costs, the cost of securing and equipping a venue, and room and board costs for Aravind's medical team and (2) Aravind's costs, which mainly involve providing medical staff. Costs vary by camp size, as indicated in Table 6. Taking into account the distribution of camps by size, we estimate Aravind's average cost per camp to be INR 30,542, or US$450, and the total cost of a camp to be INR 48,400 or US$710.[10] Thus, the average incremental revenue generated by each camp is substantially greater than both Aravind's average cost of staffing the camp and the total cost of a camp.[11]

Our camp-generated incremental revenue estimates are limited to single years during which new walk-in patients received services. This is an underestimate of the incremental revenues for at least two reasons. First, over their lifetime, these patients are likely to return multiple times to Aravind to obtain other kinds of eye care services. Second, these new patients are likely to motivate other patients to seek eye care at Aravind through word of mouth and referrals. These behaviors have been studied extensively in the context of customer lifetime value models (Kumar 2018).

Discussion of Model Validity and Robustness

Next, we discuss several aspects of model validity and robustness of our findings, including issues related to possible misspecification.

Misspecification of the functional form. The dependent variables in our models are the weekly numbers of walk-in patients, which are nonnegative integers. It is possible that the use of a regression model is inappropriate because it assumes the dependent variable is real-valued and continuous, and that models that recognize the "count" nature of the dependent variables are more appropriate. A second concern that arises is that our data contain a large number of zero values for the dependent variable. This occurs because there are no walk-in patients from smaller markets in many weeks. To address these concerns, we consider two alternative benchmark models: the negative binomial model and the Tobit model. The negative binomial model accounts for the count nature of the dependent variable. Moreover, because it allows for log-gamma-distributed unobserved heterogeneity in the Poisson mean, it accounts for potential

10. The average number of outpatients served by a camp in 2013–2014 is 260. This means the average cost to serve each M customer is $710/260, or $2.73.
11. We do not have access to contribution margins on incremental revenue.

overdispersion (in which the variance is bigger than the mean). Cameron and Trivedi (2013) note that unobserved heterogeneity that can cause overdispersion can also cause excess zeros. Our second benchmark model is the Tobit, wherein a Gaussian linear model is specified for positive realizations of the dependent variable, combined with a probit model (without covariates) that describes the censoring below at 0. This model explicitly accounts for the zeros.[12]

A challenge we faced in specifying benchmark models for our panel data is that estimation methods for negative binomial and Tobit models that incorporate spatial dependence structures are not known in the literature. Consequently, an apples-to-apples comparison with our proposed linear panel model with spatial dependence is infeasible. Instead, we specify a constrained version of our linear panel model in which the spatial dependence components are removed. This is accomplished by setting λ^{Sub} and ρ^{Sub} to zero in model 1, and λ^{Pay} and ρ^{Pay} to zero in model 2. The estimated camp effects from this constrained model are compared with the full model, as well as the benchmark models. All such models include fixed effects for markets, and they have the same number of camp effect lags as in the selected proposed model.

In Web Appendix C, Tables C1 and C2 compare the results of these three alternative models applied to the subsidized patient and paying patient data, respectively. For completeness, we also show the results of the proposed linear panel model with spatial dependence in column one (these results are reproduced from Tables 4 and 5). We note that the coefficients of different models are not directly comparable. To obtain a reasonable overall comparison, we translate the total camp effect (sum of all lags) of each model into a percentage increase over baseline walk-in traffic in the last row of Tables A1 and A2. Comparing the results of the Tobit model in column four with the other models is challenging because the estimated coefficients are interpretable as effects on walk-in traffic when the traffic is strictly positive. Accordingly, we consider the baseline traffic to be the average walk-in traffic in market-weeks when it is positive. We also show in Figure 5 the percentage increase by week for each of the models being compared.

Turning first to the results for subsidized patients (Table A1) and comparing the percentage increase in the last row, we note that the proposed model finds much larger camp effects than the benchmark models. Figure 5, Panel A, reveals that this difference occurs primarily in Camp Week + 1. However, we note that the differences between the three models that exclude spatial dependence (columns 2, 3, and 4) are relatively small. In particular, the linear and negative binomial models find identical overall increases. A similar comparison for paying patients using the last row of Table A2 shows that differences across all four models are not large. Figure 5, Panel B, also supports this conclusion.

In summary, comparing the results of models with different functional forms confirms that all models provide positive, statistically significant spillover camp effects on walk-in traffic. Moreover, the patterns of camp effect time lags are similar. The estimated absolute and relative increases in walk-in patient traffic due to camps vary across models but not dramatically. The substantive conclusion that, on average, camps produce incremental revenues in excess of costs seems robust to model specification.

Other concerns and robustness checks. A possible concern with our analysis is that some of the increase in the number of walk-in patients that is attributed to camps by our model may be due to capacity constraints at the camps. In other words, suppose a potential patient goes to a camp but the camp has already reached its capacity in terms of the number of patients it can handle. Camp staff may then instruct the patient to go to the base hospital directly, thereby causing the patient to appear as an incremental walk-in patient *because of* the camp, when in fact this patient would have been a camp patient and not a walk-in patient had the camp not reached capacity. However, we confirmed with Aravind management that all patients who arrived at a camp were accommodated. This was confirmed using the data for the 2013–2014 period, in which we observed for each camp not only the actual number of camp patients but also the planned number of patients that Aravind expected to draw. In these data, the actual number of camp patients exceeded the planned number in 20% of the camps, but all patients were treated nevertheless. In another robustness check, we found that the use of $\mathbf{W}^{\mathbf{Sub}}_{\mathbf{Exp}}$, a spatial lag matrix based on inverse exponential distance instead of contiguity, did not change the pattern of camp effects for subsidized patients or paying patients.

Discussion and Conclusions

We consider nonprofit health care organizations that use a cross-subsidization business model in which some patients are treated at market prices to generate surpluses that are used to fulfill their social mission of treating indigent patients for free or at deeply subsidized prices. Typically, in our context of low- and middle-income countries, these organizations market their services to poor patients to encourage demand but do not engage in marketing to paying patients. The question we examine is whether marketing directed to poor patients has a spillover effect on demand from paying patients. This question is of strategic importance for the financial sustainability of the cross-subsidization business model.

To study this question empirically, we use nine years of historical data from Aravind Eye Hospital, Pondicherry, on the spatial origin of paying patient traffic and marketing activities (i.e., outreach camps targeted to poor patients). Using models that allow both spatial and temporal carryover effects, we find that the occurrence of camps increases the number of walk-in

12. An alternative approach to addressing the concern about excess zeros is to use zero-inflated count models. However, these models require that we specify a model for generating the zeros that is separate from the model for generating positive values. In our case, there is no theoretical basis to specify a separate model for zero walk-in patients in a given market-week.

patients. Importantly, the walk-in patients do not directly use camp services but are indeed influenced by the camps that occur near where they live. These effects are stronger for subsidized than for paying patients. The effects occur if camps are within a ten-mile radius around the location of a patient, and they persist for three to five weeks after the camp occurs. When translated into dollars, our estimates show that the incremental revenue generated by an outreach camp exceeds the costs of organizing a camp.

Our results imply that there may be substantial synergies for nonprofit health care organizations between their marketing efforts intended to advance their social mission of serving poor patients and their revenue-generating business of serving paying patients. The findings strengthen the viability of the cross-subsidization business model that is central to Aravind's success. Our findings regarding the financial self-sufficiency of camps are potentially very important for Aravind. The findings suggest that Aravind can increase its expenditure on camps by increasing the number, duration, or frequency of camps, without being constrained by the cost of camps. These outreach activities have a very large direct impact, as indicated by the fact that almost 580,000 outreach patients were treated by Aravind in 2016–2017.[13] These findings are also useful for Aravind in its role of providing consulting to other organizations with similar business models.

Our research raises several questions that are worth pursuing in follow-up work. First, the separation of camp advertising and cannibalization effects is an important issue if in fact there is sizable cannibalization. The data available in our study did not permit us to identify cannibalization effects separately from advertising effects. It may be useful to conduct field experiments to measure the rate of cannibalization. Second, measuring the social influence between patients would be both theoretically interesting and managerially useful. We expect that word-of-mouth effects occur within each of Aravind's three segments. But it would be especially interesting to measure such effects between patients in different segments such as camp patients and paying patients because these patients have different socioeconomic profiles but live in close proximity. It is well known that one of the key econometric challenges in such work is differentiating between the role of social influence and that of observed and unobserved similarities between individuals. Such a study will require rich, individual-level socioeconomic data that could be gathered using a survey. Another possible area of investigation is whether nonprofit hospitals' community benefit activities cause similar spillover effects in the United States. If community benefit activities enhance revenues, the rationale for the tax-exempt status of these hospitals may be questioned.

Finally, we note some limitations of our research, some of which present opportunities for future work. First, the time pattern of camp effects shows an initial large effect in the week after the camp, followed by a decrease in successive weeks. This could potentially be modeled with a parametric distributed lag specification for parsimony. Second, we model successive camps in a given market as having independent effects. The advertising literature suggests that we might expect interactions between these camp effects. For instance, the possibility of diminishing returns could be considered. Finally, while we have focused on the short-term effects of camps, it would be of interest to measure the long-term effects of camps on the number of walk-in patients that hospitals receive.

[13] http://www.aravind.org/content/downloads/AECS%20Report%20201617.pdf, pp. 16–17.

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