Improving health outcomes by choosing better doctors: Evidence of social learning from rural Tanzania*

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Abstract

Households in Africa and indeed almost everywhere, face a choice of health care providers with only limited information about the relative quality of these providers. Unlike households in developed counties, however, rural African households make choices among providers of highly variable quality for illnesses that are frequently severe and they must do so without access to formal sources of information or any insurance against the consequences of bad outcomes. In spite of—or because of—these difficulties, households in rural Tanzania do learn about and react to the quality of health care providers. In this paper, I examine a two year panel of health seeking behavior for over 500 households in rural Northern Tanzania where households face choices between forty modern health care providers. This paper shows (1) that households change the way they visit new providers as they learn about quality, visiting better providers for marginally more severe illnesses and (2) households improve their outcomes as they learn about quality by choosing the appropriate doctors when they are sick. This findings have important implications for our understanding of the market for health care quality and the demand for health care more generally.

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1 Introduction

Health care systems in all countries are designed on the assumption that some form of institution is necessary to insure reasonable quality care because patients (who have no medical training) cannot discriminate between good and bad doctors. In most African countries, government regulation and public provision of subsidized health care are supposed to insure reasonable cost access to acceptable quality health care. Instead, patients in most African countries have access to health care that is of poor and variable quality. Households in Africa suffer from very severe illnesses and must choose health care providers without any formal information on health care quality and with no medical training to allow them to judge quality for themselves. At the same time, many studies have documented a willingness to pay significant fees to visit particular providers (Gertler and van der Gaag, 1990; Leonard et al., 2002). How do households form opinions about health care providers? More importantly, do these opinions bear any relationship to an objective medically-informed judgment of the quality of various health care providers? Do households choose better providers? This paper proposes that one of the ways that households form judgments on health care quality is by learning from the experiences of their neighbors and friends. Using data collected by the author in rural Tanzania, this paper shows that, when new doctors arrive, households talk about their experiences with those doctors, change the illnesses for which they visit new doctors as they learn about quality and finally, improve outcomes by choosing better doctors. We examine a two year panel of health seeking behavior for over 500 households in rural northern Tanzania where households face choices among almost 40 modern health care facilities. Staffing changes in many of these facilities mean that households face doctors of unknown quality. In order to understand the choices these households face, a team of medical doctors visited each of these facilities at least twice, intensively measuring the quality of care of each doctor present and recording the date when each doctor began working at the current location. To show that households learn from each other, I collected two additional sets of data. First, I collected self-declared characteristics of every illness episode recalled by each household and gave this information to a sample clinicians who have worked in a similar setting and asked them to code each illness by variables that measure the medical needs of each illness. This allows us differentiate, for example, between illnesses that are likely to be self-limiting and those that are likely to need immediate skilled attention. Second, we asked each household to describe illnesses from eight randomly selected households in the village. This data allows us to model the degree to which households know about illnesses in other households and to predict whether a given household would know the choices made and outcomes experienced in another household.

Leonard et al. (2009) examines the data on households' knowledge of other households illnesses and shows that (1) households can describe at least eleven other illness episodes that occurred in their village in the past year, (2) that households are more likely to recall illnesses that are responsive to quality and illnesses that resulted in visits to new health care providers. This evidence suggests that households have access to salient information about health care quality. More importantly households use this data to choose better providers.

I show that households are sensitive to changes in quality as measured by other medical doctors. By examining the types of illnesses that are reported to facilities, I show that patients suffering from illnesses that are responsive to quality are more likely to visit facilities when good doctors replace bad doctors, and less likely to visit facilities when bad doctors replace good doctors. The process of learning about quality is not instantaneous and empirical evidence suggests that households cannot learn after one visit to a provider, but must instead gather information from a larger set of outcomes.

In addition, by estimating the information available to each household at the time they sought care, and differentiating between good and bad signals of quality, I show that households are more likely to visit a provider when they are exposed to more good information about that provider and less likely to visit a provider when they are exposed to more bad information about that provider. In addition, when households are exposed to more information (either good or bad) about all the providers in their area, they are more likely to choose better providers and more likely to experience better outcomes.

Although there is little work on the role of social learning in health care, learning and technology adoption have been central issues in development economics for many decades (see Feder et al., 1985, for a review) and the role of social learning in promoting growth and technology diffusion has played a central role in the endogenous growth literature (Aghion and Howitt, 1998; Lucas, 1988; Romer, 1986). Applied research in this area has focused on learning as a process of experimentation, observation and adaptation by individuals or households. More recent research has suggested that in developing countries, observation of the activities, choices and experiences of neighbors or members of a social network is a significant source of knowledge about new technologies and their use (Conley and Udry, 2001, 2005; Foster and Rosenzweig, 1995). Much of the progress in our understanding of the role of social learning has focused on the use of agricultural technology, but recent work has highlighted the possibility that social learning can play an important role in health seeking behavior (Leonard, 2007). This paper contributes to our understanding of social learning as an institution for development by examining panel data on human capital investment in a setting in which there are frequent changes in the set of available choices, allowing us to isolate the impact of learning from that of either correlated effects or exogenous effects.[1] In addition, in this setting we can compare the behavior of households to objective measures of quality, allowing us to show that learning leads to better choices, not just different choices. These better choices can then be tied to better outcomes.

At least four features of health care demand in developing countries suggest the potential importance of learning from the experiences of others. First, patients choosing among health facilities in developing countries rarely have access to any formal sources of information about the quality of clinicians at these facilities, such as report cards or accreditation. Second, the lack of effective regulation combined with policies that emphasize the number rather than

[1]Manski (1993) differentiates patterns of similar behavior in people who share the same network into similarity in behavior because people in the same group are similar (correlated effects); similarity in behavior because people in the same group face the same environment or choices (exogenous effects); and similarly in behavior because people are learning from each other.

quality of health personnel have lead to a proliferation of medical care providers of very low quality. Recent research using instruments that measure process quality shows that the variance in clinician quality is significant even if one controls for factors a household could easily observe or discover, like clinician cadre (doctors versus clinical assistants, for example), facility type (hospitals versus dispensaries, for example) or ownership (public versus private, for example).[2] Third, because health care suffers from asymmetric information (see Arrow, 1963, 1986; Dranove and White, 1987; Gaynor, 1994; Leonard, 2003; Mooney and Ryan, 1993) and health care outcomes are not perfectly determined by the quality of care received (i.e. some sick patients are not helped by good clinicians and some are helped by bad clinicians), patients cannot assess quality from a single visit to a clinician. Fourth, although outcomes are not perfectly determined by quality, quality is an important determinant of *expected* outcomes; the probability of being cured is higher if the patient visits a good clinician. Since information on multiple outcomes of visits to a provider can help individual households assess quality, this is precisely a situation in which households should share information about their experiences and learn from this collective information.

In addition to these features of health care in developing countries, which suggest that there *should* be social learning, there is evidence that households do in fact learn about the quality of care available at multiple facilities. Leonard et al. (2002) shows that households in rural Tanzania are willing to pay significant additional costs to visit providers with above average quality of care (where quality is judged by medical teams visiting facilities) suggesting that patients know something about the quality of care available at these facilities. Leonard (2007) examines the temporal and spatial variation in the willingness to pay and shows that households act as if they are slowly adapting their beliefs about quality based on local information and experiences. This paper, by pairing panel data on household behavior with panel data on facility quality, allows a closer examination of the changes in behavior when one

[2] For a cross country comparison of variation in clinician quality, including Tanzania, see Barber et al. (2007a,b); Das and Hammer (2007a); Das and Sohnesen (2007); Leonard and Masatu (2007) as well as Chaudhury and Hammer (2004); Das and Hammer (2005, 2007b).

doctor leaves and is replaced by another doctor. In addition, by asking households to report health histories of randomly selected households in the village, the paper tests whether or not households gather information that could allow household-level learning from neighbors.

The following section introduces a theoretical model of learning about quality in health care and the subsequent choices of health facilities. section 3 discusses the data collected in Tanzania and provides some background understanding of the environment in which households make their choice of health care providers. section 4 examines the data for evidence that households gather information, learn about and adapt to the quality of care provided in their area. section 5 concludes.

2 A Model of Learning and Health Facility Choice

In this section, I introduce a model in which households learn about the quality of doctors from the results of visits to that provider and integrate this information into a model of provider choice.

2.1 Learning

The process by which individuals use new information to evaluate clinicians can be described by a model of Bayesian updating. Assume that there are two types of clinicians, good ($\phi^\star$) and bad ($\phi^\emptyset$). Before households learn anything about the clinician it has a prior belief as to the clinician's type, $\tilde{q}_t$, which is the probability that the clinician is good ($\Pr(\phi^\star)$).[3]

As the household observes outcomes, it changes its belief of clinician type. We define a variable λ, equal to the following log likelihood ratio (LLR):

$$\lambda = \log\left(\frac{\Pr(\phi^\star)}{\Pr(\phi^\emptyset)}\right) = \log\left(\frac{\tilde{q}_t}{1-\tilde{q}_t}\right) \tag{1}$$

[3]This prior could be very low (it is unlikely that the clinician is good), or very high (it is likely that the clinician is good), based on the households' previous experience and mindset. However, it cannot be either 0 or 1 because these correspond to cases in which households admit no possibility that they could be wrong about the clinician, and, in such a case, no new information could change their mind.

This LLR evolves according Bayes rule. When the household observes an outcome h_t at time t, it changes the value of λ according to the probability of that outcome given the clinician's type:

$$\lambda_{t+1} = \lambda_t + \log\left(\frac{\Pr(h_t|\phi^\star)}{\Pr(h_t|\phi^\emptyset)}\right) \tag{2}$$

Assume that there are only two possible outcomes of a visit to the provider: $h \in \{\bar{h}, \underline{h}\}$, representing cured ($\bar{h}$) and not cured ($\underline{h}$). If the clinician is good, the probability of a good outcome is $\rho^\star$ and if the clinician is bad, the probability of a good outcome is $\rho^\emptyset$. 'Good' is defined such that $\rho^\star \geq \rho^\emptyset$. Therefore, the updating rule becomes:

$$\lambda_{t+1} = \lambda_t + \begin{cases} \log\left(\frac{\rho^\star}{\rho^\emptyset}\right) & \text{if} \quad h_t = \bar{h} \\ \log\left(\frac{1-\rho^\star}{1-\rho^\emptyset}\right) & \text{if} \quad h_t = \underline{h} \end{cases} \tag{3}$$

Note that $\log(\rho^\star/\rho^\emptyset) > 0$ when $\rho^\star > \rho^\emptyset$ and therefore, no matter what the true type or the households' belief of the true type, a positive outcome means $\lambda_{t+1} > \lambda_t$ and a negative outcome means that $\lambda_{t+1} < \lambda_t$. However, since a good outcome is more likely with a good clinician than a bad clinician, the expected change in the LLR can be shown to be positive when the true type is good.

$$E\left(\lambda_{t+1} - \lambda_t|\phi = \phi^\star\right) = \rho^\star \log\left(\frac{\rho^\star}{\rho^\emptyset}\right) + (1-\rho^\star)\log\left(\frac{1-\rho^\star}{1-\rho^\emptyset}\right) > 0 \tag{4}$$

Thus, if the clinician is good, λ_t gradually increases with time (though it can go up and down with each outcome observed). We can recover the prior from the LLR since $\tilde{q}_t = \frac{e^{\lambda_t}}{1-e^{\lambda_t}}$ and since the expected value of λ_t is increasing in t when the clinician is good, $\tilde{q}_t$ must approach 1 asymptotically. In other words, with enough observations of outcomes, a household's belief about a clinician's type approaches the true value.

Note that the Bayesian increment with each new piece of information has a smaller and smaller impact on the patients belief as information accumulates. Although the prior will never be equal to exactly 1 (or zero), the closer that it gets to 1, the less it will change with each observation. This feature of Bayesian updating conforms to a simple definition of trust: once a clinician has earned their trust, patients will continue to trust the clinician despite observing one or even a string of bad outcomes.[4]

In the standard Bayesian model, each observation represents a draw from an identical distribution. In health care however, each illness is different and the probabilities of a good and bad outcome are different for each illness. Thus, $\rho^{\star}$ and $\rho^{\emptyset}$ are not constant for each observed outcome. However, as long as $\rho^{\star} \geq \rho^{\emptyset}$ for all illnesses (good clinicians are better than bad clinicians for all illnesses) and patients know the values of $\rho_j^{\star}$ and $\rho_j^{\emptyset}$ for each illness j, observation of sufficient outcomes will lead the prior to approach the true value asymptotically. Thus, for every illness where $\rho_j^{\star} > \rho_j^{\emptyset}$, the household can learn something from either good or bad outcomes. However, some illnesses are more informative than others. In particular, the expected value of the updating increment ($E\left(\lambda_{t+1} - \lambda_t\right)$) is increasing in both $\rho_j^{\star}$ and $\rho_j^{\star}/\rho_j^{\emptyset}$. If there is no cost to gathering information, households will update their prior for every possible visit, but if there is some cost to gathering information, the household will prefer to gather information about illnesses for which the value of the additional information is large. Thus, households should be more likely to recall illnesses when $\rho_j^{\star}$ and $\rho_j^{\star}/\rho_j^{\emptyset}$ are large. In addition, the expected value of additional information is much larger when t is small; when there is little information about a provider, additional information is particularly valuable.

2.2 Choosing a practitioner

The choice among multiple unknown random processes is described in the literature as the multi-armed bandit model (see Banks and Sundaram, 1994; Brezzi and Lai, 2002; Gittins and

[4] Trust in health care providers is a commonly evoked concept in health care, and is seen as an institution that partially resolves the economic problems of asymmetric information and imperfect agency (Bloom et al., 2008; Gilson, 2003, 2005). This Bayesian model goes beyond saying simply that patients prefer high quality providers to point out that they may be willing to endure significant disappointments and surprises once they have accumulated sufficient trust in a provider.

Jones, 1974, for example), and this literature highlights the importance of experimentation. When given a choice between an armed bandit (slot machine) with a known probability of payoff and an armed bandit with unknown probability of payoff, the player may choose the uncertain payoff even if the expected payoff is strictly lower. It is rational to choose the unknown machine even when the expected payoff is lower, because the player has the choice to return to the original machine, but can add to his or her knowledge about the unknown machine (and maybe learn that it is better). Health care in Africa is similar to this model in the sense that switching costs are very low (unlike the choice of insurance provider in the US), but dissimilar in the sense that experimentation can have catastrophic costs. I assume that either, there is no experimentation motive because households can learn something about new providers by watching their neighbors or that households can experiment with non-severe illnesses.

In addition, I assume that there is no strategic behavior among households. Illnesses tend to happen in unpredictable intervals and often require health care in a timely manner. Thus, it would be dangerous for a household to sit with an illness while they wait to see if a neighbor is willing to experiment with a new provider. Furthermore, once a household has visited a provider there is no reason to hide the information from their neighbor. The information learned from a visit to a new provider may have value to other households, but there is no cost to the first household for providing this information. There are cases in Africa where households do not share information, but this does not appear to be because they could sell the information, but rather because there is some cost to disseminating or gathering information. In Africa and in many developing countries, households are reluctant to talk about anything that is tied to income even with their neighbors and researchers are frequently surprised about how little farmers know about their neighbors experiences with income generating technologies.[5] In some cases it is taboo to be perceived to know too much about your neighbor, because then your jealously can be blamed for any bad luck

[5] Conley and Udry (2005) find that farmers know almost nothing about the details of their neighbors activities even when they appear to learn from the results of these same activities.

they experience. Among the Maasai in northern Tanzania, extended arguments can ensue if your neighbor suspects you of counting his cattle. Among this same population, however, we experienced no reluctance to talk about health care experiences. We assume that households are unlikely to talk about embarrassing illnesses, but this leaves a very large set of illnesses about which information can be shared freely.

Thus, we assume that households will choose the provider with the highest expected payoff without regard to experimentation or strategic behavior of other households. The value of visiting a provider is a function of both the probability of a cure and the value of a cure. Following Leonard and Graff Zivin (2005), the expected value of health care from visiting provider k at time t for an individual with illness j is a function of $\rho_j^\star$ (probability of a cure with the correct diagnosis), $\rho_j^\emptyset$ (probability of a cure with incorrect diagnosis) and the household's belief of the quality of doctor k at time t, $\tilde{q}_{kt}$. $\tilde{q}_{kt}$ can be interpreted as the probability that the doctor will give the correct diagnosis. Thus,

$$EU_{jkt} = \tilde{q}_{kt} \underbrace{\left(\rho_j^\star \bar{U}_j + (1-\rho_j^\star)\underline{U}_j\right)}_{\text{EU under corect diagnosis}} + (1-\tilde{q}_{kt}) \underbrace{\left(\rho_j^\emptyset \bar{U}_j + (1-\rho_j^\emptyset)\underline{U}_j\right)}_{\text{EU under wrong diagnosis}} \tag{5}$$

$$\text{where} \qquad \bar{U}_j = U[\bar{h}_j, (I(\bar{h}_j) - C)] \qquad \text{and} \qquad \underline{U} = U[\underline{h}_j, (I(\underline{h}_j) - C)]$$

$\bar{U}_j$ is the utility if the patient is cured and $\underline{U}_j$ is the utility if the patient is not cured. The utility of health care is a function of the outcome ($h_j \in \{\bar{h}_j, \underline{h}_j\}$), full income for the outcome ($I_j \in \{I(\bar{h}_j), I(\underline{h}_j)\}$) and any cash costs associated with the visit (C). Note that these costs are assumed to to vary with illness condition, which is not strictly true in the real world. I assume a separable utility function, such that $U(H) = V[H, I(H)] - C$, and therefore,

$$EU_{jkt} = \tilde{q}_{kt} \left(\rho_j^\star \bar{V}_j + (1-\rho_j^\star)\underline{V}_j\right) + (1-\tilde{q}_{kt}) \left(\rho_j^\emptyset \bar{V}_j + (1-\rho_j^\emptyset)\underline{V}_j\right) - C \tag{6}$$

When the patient is choosing between two different doctors, he or she will visit the doctor who provides the greater expected utility. The difference in the utility of visiting provider

$k = 1$ (with uncertain quality $\tilde{q}_{1t}$) compared to provider $k = 2$ (with certain quality q_2) is

$$EU_{j,(k=1),t} - EU_{j,(k=2),t} = (\tilde{q}_{1t} - q_2) \cdot (\rho_j^\star - \rho_j^\emptyset) \left(\bar{V}_j - \underline{V}_j\right) - (C_1 - C_2) \tag{7}$$

Define a variable $s_j = (\rho_j^\star - \rho_j^\emptyset) \left(\bar{V}_j - \underline{V}_j\right)$, as a measure of quality responsiveness for each illness j. Illnesses are more responsive to quality if the difference in probability of a cure with a correct diagnosis over incorrect diagnosis $(\rho_j^\star - \rho_j^\emptyset)$ is higher or if the net value of a correct diagnosis $\left(\bar{V}_j - \underline{V}_j\right)$ is higher.

Clearly, households will always visit a provider who is both better and less expensive than all other providers. In addition, households will never visit lower quality providers who are more expensive or further away than a high quality provider. However, in general, households face a tradeoff between quality and expense. This tradeoff exists both because high quality providers frequently (though not always) charge higher fees, but also because there are fewer high quality providers and therefore, in the rural areas, average travel costs must be higher.

We focus therefore on relevant pairs of providers, where one is both better and more expensive (in terms of cash costs or travel) than the other. For all relevant pairs of providers available to a household, there exists an illness type $j = J$ such that the household is indifferent between the two providers:

$$EU_{J,(k=1),t} == EU_{J,(k=2),t} : (\tilde{q}_{1t} - q_2)s_J - (C_1 - C_2) == 0 \tag{8}$$

Ordering the providers so that the first provider is of lower quality than the second ($\tilde{q}_{1t} < q_2$), then for all illnesses with greater quality responsiveness than illness J ($\forall i : s_i > s_J$), the household will prefer the better provider ($EU_{i,(k=1),t} < EU_{i,(k=2),t}$). For all illnesses with lower quality responsiveness than illness J ($\forall i : s_i < s_J$), the household will prefer the lower quality (but cheaper) provider ($EU_{i,(k=1),t} > EU_{i,(k=2),t}$).

The highest quality providers in the sample are the urban private hospitals and the quality at these facilities is not changing over time. Thus, we focus on the choice to visit a provider who is nearer than these high quality providers. Even though the quality of a local provider is lower than the quality of some urban hospitals, the cost is much lower and therefore households will chose to visit the local provider for a wide range of illnesses. The expected quality responsiveness of all illnesses reported to the first provider is therefore a function of the density of illness responsiveness from the least responsive illness ($j = \underline{j}$) up to the indifference illness ($j = J$):

$$E(s|EU_{i,(k=1),t} \geq EU_{i,(k=2),t}) = \int_{j=\underline{j}}^{J} s_j \cdot ds$$
$$\text{where} \qquad J : s_J = \frac{(C_1 - C_2)}{\tilde{q}_{1t} - q_2}, \qquad \tilde{q}_{1t} < q_2 \qquad \text{and} \qquad C_1 < C_2$$

When the household is learning about the quality of the first doctor, only $\tilde{q}_{1t}$ is changing and the costs of both providers and the quality of the second provider is constant. Therefore $\partial s_J / \partial \tilde{q}_{1t} > 0$: the indifference value of quality responsiveness increases as beliefs about quality increase. In other words, the expected value of quality responsiveness at the first provider is increasing if households raise their opinion of a doctor ($\frac{\partial E(s)}{\partial \tilde{q}_{1t}} > 0$ if $q_1 > \tilde{q}_{1t}$) and and decreasing if households lower their opinion of the doctor ($\frac{\partial E(s)}{\partial \tilde{q}_{1t}} < 0$ if $q_1 < \tilde{q}_{1t}$).

Thus, the expected value of quality responsiveness is a function of the beliefs that households hold about quality at the facility as well as a function of the cost of visiting that facility (including travel costs and fees and drug costs). The expected value of illness responsiveness for illnesses resulting in a visit to provider k, from household i, at time t, is represented in a reduced form representation as

$$E\left(s_{ikt}\right) = f(\tilde{q}_{1t}) + \epsilon_{ik} + \epsilon_{ikt} \tag{9}$$

where ϵ_{ik} represents a household-facility fixed effect and ϵ_{ikt} is a normal disturbance. The fact that villages can choose other facilities (with known quality) is included in the village-facility fixed effect.

The theory provides us with a simple, intuitive test of learning: when households are faced with a provider of unknown quality (a new provider) and they have an alternative choice of a known high-quality high-cost provider, the average quality responsiveness of illnesses that result in a visit to the unknown provider should increase if that provider is above average quality and decrease if that provider is below average quality. Note that the unknown, local provider does not have to be better than the known high quality provider, only better than the average local provider. The uninformed prior expectation of quality for a new provider should simply be the average quality, so any provider who is above average will see gains in "market share" over time. Although households might learn about the quality of more than one provider at the same time, as long as the changes in information in one provider are independent of the changes at another provider, this same pattern should hold.

3 Description of the Data

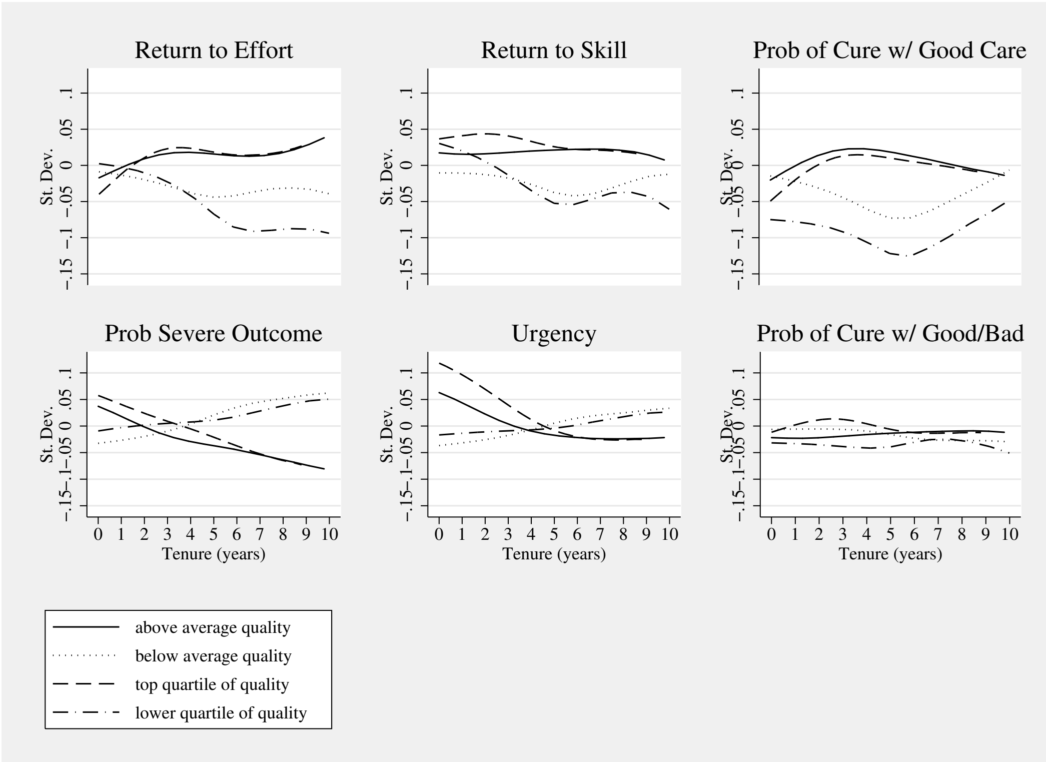
The research area comprises the northern part of Monduli district and the Western part of Arumeru district (both in Arusha region) forming a region bounded to the north by the Kenyan border and to the west by Lake Natron and Ngorongoro crater. Almost all travel from the research area feeds into Arusha municipality. The research area was deliberately chosen because the natural and geographic borders define a region where most travel is either within the region or through the town of Arusha. Since Arusha town contains at least two very high quality health care providers, it is possible to enumerate almost all health facilities that are ever visited by residents of the research region.

The terrain in the research area varies from sparsely populated semi-arid to more densely populated rain-fed regions on the slopes of Mount Meru and Mount Monduli. The primary occupation in the semi-arid region is cattle herding, and the areas with better rainfall are intercropped with maize and beans, with some coffee grown on the slopes of Mount Meru. Most of the residents of the research area are either Maasai or Warusha, two clans with a common language (Kimaasai).

Households in the research area can visit nearby modern health care providers who operate from government and church–operated clinics or health centers. In addition, households can choose to visit more distant clinics and health centers or travel to Arusha or Monduli towns and visit government, church–operated, private, parastatal or Islamic hospitals and health centers. Households can also choose not to visit modern health care providers and instead buy medicines directly from pharmacists, visit traditional healers, treat themselves with folk remedies, or not seek health care at all. Approximately 82.5% of the population of the research area lives within 5 kilometers (kms) of a health facility. To access high quality care most patients will have to visit the urban area of Arusha, at a travel time of up to 6.9 hours (145 km) for the most remote residents in the sample (Klemick et al., 2009).

The quality of local care available to households in the research area varies significantly, as documented in recent papers from the research area (Leonard and Masatu, 2005, 2007; Leonard et al., 2007). Rural health clinics are generally staffed with one "doctor" who is either a clinical officer or clinical assistant, and one nurse. Clinical assistants have an elementary school education and three years of medical training. Clinical officers traditionally have O level (four years of secondary schooling) education and two years of medical training. Occasionally only a nurse is present. Health centers are staffed with two doctors, of whom one is usually an assistant medical officer. AMOs are clinical officers with two additional years of training. Hospitals are staffed with a wide variety of clinicians, but there is always a full medical doctor present. MOs have both an A level education (6 years of secondary schooling) and 5 five years of university–level medical training. The average observed doctor has been at his current post for 6.3 years and there is no correlation between tenure and quality either in cross section or for the same doctors over time.

Although quality varies significantly between the cadres of doctors, the variance in quality within doctors of exactly the same training is also significant. In addition, the practical consequence of this variance is severe. Klemick et al. (2009) suggest that 91% percent of doctors can correctly diagnoses malaria, 11.5% can correctly diagnose malaria with complications, 62.3% can correctly diagnose a woman suffering from pelvic inflammatory disease, 64.8% can correctly diagnose the causes of infant diarrhea, 82% can correctly diagnose pneumonia, 79% can correctly diagnose a case of the flu and 76.2% could correctly diagnose a worm infestation. Since these number reflect the performance of doctors under the best circumstances, they are upper bounds on quality and actual practice quality is much lower (Leonard and Masatu, 2005).



3.1 Health Seeking Behavior

The research team interviewed 502 randomly selected households from 22 villages in 20 wards of Arusha region of northern Tanzania. Each household was interviewed twice over the period 2002 to 2003. Households were chosen by a stratified random procedure: one village was selected in each ward in the research area.[6] Each village is comprised of 1 to 5 subvillages and each subvillage contains 2 to 5 cells. Cells are groupings of approximately 20 households. We randomly chose two subvillages in each village, two cells from one subvillage and one cell from the other subvillage.[7] We interviewed eight households in each cell.[8] This process insures a sample of households that are geographically dispersed within each village.

In addition to socio-demographic characteristics of all members of each household, the

[6]We over-sampled villages in two wards that experienced a change in their local health facility during the first round of data collection.

[7]For villages with only one subvillage, all cells were drawn from the same subvillage.

[8]The response rate was therefore 502/528 or 95%. Twenty-four of these missing households had no adults present on the day of the survey or the make-up day. Two households refused consent.

survey team collected information on the health history of the household over the past year. We collected information on the symptoms and self-declared severity of the illness, the patient's ability to perform a series of activities of daily living (ADLs) before and after the onset of the illness, the number of days sick and number of days bedridden before seeking care, the first provider visited (if any), the diagnosis, and the outcome. With two rounds of data collection almost exactly a year apart, the survey has data on many if not most of the health episodes suffered by a household over a two-year period.

Following a process first demonstrated in Leonard (2003), all of the information about health episodes except the provider chosen, diagnosis and outcome was transcribed onto cards and copies of these cards were given to clinicians who practice medicine in this region. These clinicians graded each illness by the following criteria (on a scale of 1 to 10):

- responsiveness to effort (the degree to which more effort in examination improves the chances of a successful outcome);
- responsiveness to skill available at an untrained provider (the degree to which untrained providers with experience can properly diagnose and treat the illness);
- responsiveness to skill available at a dispensary (the degree to which low levels of training and equipment are adequate to properly diagnose and treat the illness);
- responsiveness to skill available at a hospital (the degree to which training and better laboratories or other equipment improve the chances of a successful outcome);
- chance of a successful outcome with the best possible care (the chance of recovery if a clinician provides all necessary effort and has all necessary skill);
- chance of a successful outcome with poor quality care (the chance of recovery if a clinician provides no effort or has no skill);
- severity (the degree to which a severe outcome is possible);

- urgency (the degree to which the patient requires immediate medical attention).

Thirty-seven clinicians examined the full set of illnesses, and at least three different clinicians coded each illness. We examine seven scores derived from the scores above: (1) the responsiveness to effort, (2) the responsiveness to skill (the net gain from skill available at a hospital over skill available at an untrained provider), (3) chance of recovery with the best possible care ($\rho^{\star}$), (4) severity, (5) urgency, (6) the ratio of the chance of recovery with the best possible care to the chance of recovery with poor care ($\rho^{\star}/\rho^{\emptyset}$).

Since the illnesses were randomly assigned to clinicians for coding, we create scores for each illness by standardizing these seven scores for each coder and then averaging for each illness episode over all clinician coders.

3.2 Health Provider Quality

At the same time, every modern medical facility in the research area—including those in nearby urban areas—was visited by a medical team at least twice over the course of the data collection period. These visits generated information about the quality of health care provided by every doctor who was present and doing outpatient consultation during the site visit. We use the measures of practice quality derived in Leonard et al. (2007) as our measure of quality. In addition, for each doctor observed, we have data on the date at which that doctor started working at that facility. Using this panel data we can reconstruct the history of postings for each of the facilities in our sample, with data on which doctor was present at what moment in time. Therefore, for every visit to a modern provider, we can assign the type of facility (clinic, health center or hospital), and the quality and tenure of all medical personnel on duty.

3.3 Learning from Neighbors

As part of the household survey, we also asked each household whether they knew any members of eight randomly selected households from their village drawn from our village sample. We selected three random households from the same cell, three from the same subvillage but different cell and two from the same village but different subvillage. Thus, every household in the survey knew at least one of the given households, and almost no households knew all of the households. If they said they knew any members of the other household, they were asked if they could recall any health events from that household. If they could recall any health events, they were asked the name of the patient (or the relationship to someone they could name), the symptoms and the location visited. We refer to the household reporting information about their neighbors as the *respondent* household and the household about which information is reported as the *subject* household. Each individual household, however, is both a respondent and a subject household. The set of subject households was randomly assigned to respondent households in each of the two rounds of data collection separately and was not designed to be reciprocal.

For privacy reasons, the enumerator asking questions of the respondent household only knew the names of the adults in the subject household, and therefore could not clarify any of the information provided during the interview. After the interview, however, we could examine information on health episodes from both the subject and respondent. Taking the subject reports as correct, we tried to match all illness episodes reported by the respondent to a subject report. In other words, given that household A recalled that household B had suffered from a particular illness, we looked for evidence of that particular illness in our data from household B. The data was matched when the name (or relationship) and the symptoms or location matched a unique illness among the subject reports (see Leonard et al., 2009, for more details on this process).

4 Analysis

In this section we examine first, the reasons why one household is likely to report the illness suffered by another household, then the changes in patterns of health seeking as the tenure of doctors increases and then the changes in the patterns of health seeking as households gather information about quality.

4.1 Gathering information from neighbors

Here we summarize the reasons why households report the illnesses suffered by other households as detailed in Leonard et al. (2009). Although it is possible that households know about more illnesses than they choose to report and likely that at some point in time they knew about illnesses that they do not report, we seek to understand why some illnesses are more likely to be reported than others. I use a random effect probit model with random effects for each subject household, which controls for features of subject household, village, and local health providers. Since one way in which households may come to know about each other is through information about health care visits, we include all subject households in the analysis, not just the subject households that the respondent household says they know. The results are qualitatively the same if we only include subject households that are known by the respondent households.

Table 1 shows the results of two random effect probit models on whether the respondent household reported an illness from the subject household. Column 1 shows the results reported in Leonard et al. (2009). Households are much more likely to know other households that are near to them and therefore more likely to know about their illnesses. They are more likely to know about severe illnesses and illnesses that lasted a long time. After controlling for self-declared severity, households are more likely to know about illnesses that are responsive to quality ($\rho^{\star}$) but less likely to know about those that are differentially responsive to high quality ($\rho^{\star}/\rho^{\emptyset}$). Households are less likely to know about illnesses that resulted in visits to

Table 1: Determinants of whether a household reports the illness of a neighbor

	Dep Var: whether the respondent household reports an illness given the set of all illnesses recalled by subject households (0/1)			
	(1)		(2)	
Distance between paired households				
same cell	0.906	[0.053]***	0.905	[0.053]***
same subvillage	0.161	[0.069]**	0.161	[0.069]**
Self-Described Illness Characteristics				
Mild illness	-0.042	[0.138]	-0.05	[0.138]
Average illness	0.095	[0.121]	0.084	[0.121]
Very sick	0.235	[0.123]*	0.222	[0.123]*
"could have died"	0.455	[0.143]***	0.441	[0.143]***
days since sick (log)	-0.099	[0.012]***	-0.099	[0.012]***
Clinically-coded Illness Characteristics				
$\rho^{\star}$	0.123	[0.041]***	0.124	[0.042]***
$\rho^{\star}/\rho^{\emptyset}$	-0.111	[0.040]***	-0.114	[0.039]***
resp. to effort	-0.035	[0.037]	-0.042	[0.037]
severity	0.032	[0.057]	0.035	[0.056]
urgency	0.05	[0.055]	0.053	[0.054]
net resp. to skill, hosp.	0.095	[0.041]**	0.093	[0.041]**
net resp. to skill, clin.	-0.003	[0.038]	-0.003	[0.038]
Location of health care				
traditional healer	-0.005	[0.222]	-0.015	[0.222]
folk cure	-0.188	[0.096]**	-0.191	[0.096]**
pharmacy	-0.264	[0.126]**	-0.269	[0.126]**
non-hospital	-0.193	[0.079]**	-0.156	[0.075]**
hospital	0.218	[0.083]***	0.215	[0.083]***
new clinician	0.104	[0.062]*		
Outcome				
died	-0.226	[0.320]	-0.264	[0.324]
cured	0.084	[0.086]	0.09	[0.086]
not cured	0.41	[0.109]***	0.42	[0.109]***
referral	0.37	[0.242]	0.375	[0.242]
visited other facility	0.485	[0.135]***	0.481	[0.135]***
would return	0.231	[0.069]***	0.232	[0.069]***
Constant	-2.476	[0.152]***	-2.466	[0.151]***
Observations	25186		25186	
# of unique hhs.	493		493	

Random effects probit model of the probability that a respondent household will mention and correctly describe key details of an illness in the subject household, from among all the illnesses recalled by the subject household. Random effects included for each unique subject household.

‡new doctor: average tenure at facility is less than two years.

Standard errors shown in brackets, * indicates significance at the 10% level. See text for description of the independent variables.

pharmacies or small facilities or for which the patient simply took a folk cure. They are more likely to know about illnesses that resulted in visits to providers. Although they are not more likely to know about illnesses that resulted in visits to small providers in general, they are more likely to recall these visits if the provider at that facility is new (has been there less than two years). There are more likely to recall illnesses that resulted in the patient no-being cured, visiting another facility or stating that they would return to the facility if they suffered from the same illness in the future.

Column 2 of Table 1 shows the same regression as column one with the exception that we drop the variable "new clinician." We do this because we want to be able to predict the total amount of information gathered about a provider over time, to see if this changes behavior. This commutative level should not depend on whether a clinician is new.

4.2 Changes in the Choice of Provider as Households learn about new Providers

In order to test whether households are adapting their behavior as they learn about the quality of providers we look a series of regressions based on the reduced form equation derived above:

$$E\left(s_{ikt}\right) = f(\tilde{q}_{1t}) + \epsilon_{ik} + \epsilon_{ikt}$$

We examine three different ways of measuring $\tilde{q}_{1t}$. First, in the first row of Table 2, we proxy for $\tilde{q}_{1t}$ with the average quality of care provided at each facility, as measured by doctors on our team. This is based on the assumption that households learn instantaneously about new the quality of new doctors. Second, we proxy for $\tilde{q}_{1t}$ by interacting the quartile of actual average quality at each facility with the log of average tenure. These results for this regression are shown in the third through sixth rows of Table 2. Third, we create measures of the quantity of good and bad information about each facility assuming that the prior evolves in an approximately linear fashion with information. These results are shown in Table 3.

4.2.1 Choice of provider and the objectively measured quality of care

Table 2 presents evidence that households adjust to the arrival of new doctors over time as if they were gradually learning about their quality. In theory we would expect a household to choose to visit a new doctor as if that doctor was of average quality when the doctor first arrived at a facility. As time passed and the household gathered more information, we expect the behavior of the household to resemble the behavior that would be expected if they knew quality for certain. Although we know the quality of every doctor working in these facilities over the two year period, we do not know what prior patients form over new providers and whether it takes into account the history at the local facility, history in similar facilities or some other variables. Therefore for each regression estimating the expected value of severity at each facility, we include fixed effects for all village-facility pairs. Our regression measures *changes* in the use of facilities, not the *levels* of use.

Columns 1, 3, 5, 7, 9 and 11 of Table 2 show that expected value of the responsiveness to medical quality, responsiveness to skill and the probability of a cure with good care are all increasing with the quality of doctors at facilities, whereas the ratio of the probability of a cure under good and bad care, the severity and the urgency of the illness are not responsive to quality. Since these regressions control for facility fixed effects, these results cannot show that some illnesses are more likely to be reported at some facilities, but that some illnesses are more likely to be reported to any facilities when quality exceeds average quality for that facility: patients are sensitive to changes in quality.

The level of quality at any given facility does not vary as the tenure of a doctor increases, however, the beliefs of households about the level of quality can vary, particularly when doctors are relatively new. Columns 2, 4, 6, 8, 10 and 12 examine the changes in the types of illnesses reported to facilities as tenure increases. We divide doctors into four types of doctors corresponding to the quartiles of observed quality in the data. For each type of doctor, we include the log of tenure as an independent variable. We expect the quality responsiveness of illnesses to increase with tenure for doctors who are above average, and to

Table 2: Evidence of households adjusting to doctor quality as tenure increases

	illness responsiveness to											
	medical effort		medical skill		$\rho^\star$		severity		urgency		$\frac{\rho^\star}{\rho^\emptyset}$	
practice quality	0.229		0.582		0.377		-0.055		-0.122		0.002	
	[0.090]*		[0.187]*		[0.097]*		[0.121]		[0.136]		[0.123]	
Quartiles of Practice Quality interacted with log of tenure												
4th quartile		0.286		0.633		0.365		0.031		0.009		0.049
		[0.055]*		[0.115]*		[0.059]*		[0.075]		[0.084]		[0.076]
3rd quartile		0.232		0.542		0.26		0.081		0.02		0.11
		[0.058]*		[0.121]*		[0.062]*		[0.079]		[0.089]		[0.080]
2nd quartile		0.076		0.179		0.084		-0.04		-0.062		0.08
		[0.067]		[0.141]		[0.072]		[0.092]		[0.103]		[0.093]
1st quartile		0.054		0.02		0.061		-0.01		-0.182		0.039
		[0.107]		[0.225]		[0.115]		[0.146]		[0.164]		[0.148]
Constant	7.868	7.652	5.977	5.509	8.769	8.511	4.077	4.047	4.022	4.059	3.195	3.113
	[0.030]*	[0.055]*	[0.064]*	[0.116]*	[0.033]*	[0.060]*	[0.041]*	[0.075]*	[0.046]*	[0.085]*	[0.042]*	[0.076]*
Observations	1384	1384	1362	1362	1382	1382	1380	1380	1383	1383	1361	1361

Fixed effect regression of six medically–defined characteristics of illnesses on the average quality of providers at the facility chosen. The regression controls for 128 village-facility pairs using fixed effects. Quality is included directly in columns 1, 3, 5, and 7 and interacted with the log of average tenure in columns 2, 4, 6 and 8.

decrease with tenure for doctors who are below average. In fact, we find that the average quality responsiveness (as measured by responsiveness to effort and skill and the probability of a cure with high quality care) is increasing with tenure for the third and fourth quartiles of quality, but flat for the first and second quartiles. The quality responsiveness as measured by severity, urgency and the ratio of the probability of cure with high and low quality ($\rho^{\star}/\rho^{\emptyset}$), do not change with tenure for any quartile of quality. Thus, as households learn about quality, they are changing the types of illnesses that they report at those facilities if the doctor turns out to be good, but they continue to avoid doctors who are bad.

4.2.2 Choice of provider and gathered information

In this section we look at the changes in behavior, not as a function of tenure, but as a function of the cumulative information gathered about a particular facility. Households can learn about the quality of a given facility from the earlier experiences of others if those households and individuals suffered from illness episodes that resulted in visits to that same facility *and* if at least one doctor remains on staff from the earlier visit. If the information available to a household changes their beliefs about quality, then it will change the expected value of the quality responsiveness of illnesses reported at any given provider. Thus, in the same way that we examined the expected value of quality responsiveness as a function of tenure, we can examine the expected value of quality responsiveness as a function of the cumulative information about a particular provider.

Illnesses relevant to a particular decision can be weighted by the probability that the household would know about it. To weight illnesses we use the coefficients derived from the second specification of the probit model discussed in Table 1. Since, even if households forget about the details of a particular illness, they are likely to remember the implications of the illness we assume that households learn about illnesses almost immediately after they happen and set the log of days since the illness occurred to zero when we predict the probability that each household would know about any given illness. Households are assumed to hear about previous illnesses in their own household with 100% certainty. In addition, relevant illnesses can generate both positive and negative information. We predict the probability that a household would give negative or positive feedback by modeling whether a household said they would return to the facility as a function of the outcome of the illness (died, cured, not cured, visited other facility, and referred) and village–facility level random effects. Thus each relevant illness is assigned a probability that the household would have gathered information on that illness as well as assigned a probability that the result would be seen as good or bad news about the quality of the provider. In addition to a household level measure of information, we generate a village level information score in which the probability of hearing about an illness is set to one for every household. This assumes that, even if households do not hear about an illness, they become aware of the implications of the results of that illness relatively easily.

Table 3 shows that there is evidence of learning in the patterns shown for responsiveness to effort and skill and for the probability of being cured with high quality care, but no evidence for learning in the patterns for severity, urgency and the ratio of the probability of being cured with good and bad care ($\rho^{\star}/\rho^{\emptyset}$). Table 3 also shows that village-level learning is more likely to be a source of information than household-level learning. Good news at the village level increases the expected value of quality responsiveness for responsiveness to effort and skill and probability of a cure with high quality care, and bad news at the village level decreases the expected value of quality responsiveness. Note that the expected value of quality responsiveness is increasing with tenure as well, even after controlling for exposure to cumulative news about a given provider.

4.3 Changes in outcomes as households learn

Table 4 examines the outcomes of illness episodes as a result of village level news about relevant providers. For this analysis we create an index of news about all providers relevant to a given village. Thus, the index is a count of all previous visits to providers with at

Table 3: Adapting to Information: Choice

	Responsiveness to effort	skill	$\rho^\star$	severity	urgency	$\rho^\star/\rho^\emptyset$
Cumulative relevant information about the provider visited						
household: good	-0.022	-0.084	-0.006	-0.04	-0.057	0.055
	[0.030]	[0.062]	[0.032]	[0.041]	[0.046]	[0.041]
household: bad	0.177	0.065	0.062	-0.095	0.154	-0.359
	[0.161]	[0.333]	[0.174]	[0.219]	[0.247]	[0.219]
village: good	0.021	0.087	0.025	-0.016	-0.006	-0.004
	[0.009]*	[0.018]*	[0.009]*	[0.012]	[0.013]	[0.012]
village: bad	-0.093	-0.558	-0.136	0.063	0.048	0.086
	[0.060]	[0.124]*	[0.065]*	[0.081]	[0.092]	[0.082]
log of tenure	0.143	0.415	0.193	0.046	-0.031	0.048
	[0.042]*	[0.087]*	[0.046]*	[0.057]	[0.065]	[0.057]
Constant	7.612	5.501	8.476	4.176	4.084	3.045
	[0.062]*	[0.129]*	[0.067]*	[0.085]*	[0.096]*	[0.085]*
Observations	1371	1349	1369	1368	1370	1348

Fixed effect regressions with fixed effect for each village facility pair (128 unique pairs). Each observation represents a household with a given illness (and illness characteristics) choosing to visit a health care provider. Cumulative news is the sum of all information generated by previous visits to the provider chosen when at least one of the doctors at a facility was on staff during both visits. Household news is weighted by the probability that the health seeking households would have heard of the illness given the model of information gathering represented by column four of Table 1, except own household visits which are given a weight of 1. Village news weighs all information equally. Is the probability that a household would return given the outcome, bad news is the probability that a household would not return given the outcome.

Table 4: Adapting to Information: Outcomes

	Outcome of Treatment					would	Quality of
	died	cured	other fac.	not cured	referral	return	fac. chosen
resp. to effort	0.171	0.059	0.014	-0.135	0.103	0.049	-0.009
	[0.187]	[0.039]	[0.065]	[0.048]*	[0.171]	[0.041]	[0.011]
resp. to skill	0.013	-0.033	-0.007	0.097	0.23	-0.014	0.004
	[0.081]	[0.019]*	[0.033]	[0.026]*	[0.100]*	[0.020]	[0.005]
$\rho^{\star}$	-0.037	-0.065	-0.003	0.002	0.001	-0.072	0.021
	[0.186]	[0.039]*	[0.067]	[0.051]	[0.195]	[0.042]*	[0.011]*
severity	-0.05	-0.07	0.22	0.036	-0.137	0.039	0.008
	[0.176]	[0.042]*	[0.068]*	[0.056]	[0.155]	[0.046]	[0.011]
urgency	0.132	0.002	-0.057	0.074	0.189	-0.035	-0.006
	[0.145]	[0.037]	[0.062]	[0.049]	[0.142]	[0.040]	[0.010]
village cumulative news about all relevant providers							
	0.009	0.007	-0.003	0	0.009	0.005	0.002
	[0.007]	[0.002]*	[0.003]	[0.002]	[0.005]*	[0.002]*	[0.000]*
Constant	-5.457	1.381	-2.827	-1.716	-6.087	1.26	-0.229
	[1.839]*	[0.336]*	[0.562]*	[0.431]*	[2.286]*	[0.350]*	[0.090]*
Observations	2080	2080	2080	2080	2080	2080	1347
Unique pairs	219	219	219	219	219	219	128

Columns one through six are random effect probit regressions of six discrete outcomes: (1) the patient died, (2) is cured, (3) chose to visit another facility after the first visit, (4) was not cured but has not visited another facility, (5) was referred to another facility, and (6) the separate category of whether or not they would return for a similar condition. Column 7 is a fixed effect regression of the average practice quality of the facility visited. Each regression controls for all village facility pairs. Columns one through six include all illnesses whether or not a modern health care provider was chosen. Column seven includes only visits to modern health care providers.

least one doctor in common within the set of possible facilities for a given household when they suffer from an illness. Since all information should improve decision making, we do not differentiate by good or bad news. After controlling for the characteristics of an illness, and village-facility random effects, we expect to see that households with more information make better choices and therefore experience better outcomes. Table 4 shows that households with more information are more likely to be cured, more likely to be referred and more likely to be satisfied (say they would be willing to return). In addition, households with more information choose to visit providers who have higher quality on average (after controlling for village–facility level fixed effects). Although referrals appear to be seen as negative information, they signal that a household had an ambitious belief as to the quality present at a given facility. Even if a referral is a disappointment, it signals ex ante confidence in a provider.

5 Conclusion

This paper shows that households gather information about the health experiences of their neighbors in a way that should generate useful information about health care quality. Given that households are unlikely to be able to assess the quality of care provided by any given practitioner from one visit to that practitioner, households should begin to assess quality by examining the outcomes of visits to providers. We show that households are more likely to report the details of illnesses if those illnesses are severe, if they resulted in visits to providers with unknown quality and if they generated unexpected outcomes. Since the severity of outcomes is highly correlated with the information content of outcomes (as measured by the ratio of the probability of a cure with high quality care to the probability of a cure with low quality care), households are also more likely to report the details of illnesses with high information content.

Although this evidence cannot prove that households gather information for the purpose of learning about quality, it is clear that this information, once gathered, can be used to learn about quality. This paper shows that households treat facilities with new doctors differently than facilities with doctors of longer tenure. The types of illnesses that are reported at facilities change as the tenure of a doctor increases. If the doctor is of high quality (as measured by medical evaluation, not by the patients themselves) then the average quality responsiveness of illnesses increases with tenure. If the doctor is below average quality, the patterns of illnesses reported do not appear to change with tenure.

In addition, the data show that the average quality responsiveness of illnesses is increasing in the stock of good news about doctors at a particular location and decreasing the stock of bad news about doctors. This suggests that households react to the news that is being gathered. In addition to reacting to information, the data show that households make better decisions as a result of the information gathered. Households that are exposed to more information about providers from which they can can choose, make choices that result in an increased likelihood of being cured and end up choosing doctors with higher quality.

In this paper we examine six possible measures of quality responsiveness: the responsiveness to medical effort, responsiveness to medical skill, the probability that an illness will be cured with high quality medical care, the ratio of that probability to the probability that it would be cured with low quality medical care, the severity of possible outcomes and the urgency of care. It is not clear, a priori, how each of the factors should be related to the search for quality, except that we do not expect households to be more likely to visit high quality providers when illnesses require urgent care, since high quality facilities are almost always further than regular facilities. We find that the responsiveness to medical effort, responsiveness to skill and the probability of a cure with high quality care all help to describe a household's search for high quality care. This does not suggest that households know these probabilities, but rather that households follow a decision criteria that can be partially described by knowledge of these probabilities.

In addition, we do not find evidence that households learn about quality independently.

The patterns of behavior followed by households appear to track all illnesses experienced in the village, even though it is clear that they do not know about all illnesses experienced in their village. This evidence confirms a finding from Leonard (2007) that households that live within 5 kms of each other exhibit strong similarity in behavior, a limit similar to the maximum distance between subvillages in this setting. This finding, in turn, suggests that information spreads between households in the form of advice as well as in the form of raw information about illnesses and their outcomes. Advice about health seeking appears to spread more extensively across villages and is therefore not limited to the number of illnesses experience in the immediate vicinity of a household, but it is still limited by the number of information generating illnesses experienced in the village.

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