The Struggle for Digital Inclusion: Phones, Healthcare, and Marginalisation in Rural India

Marco J. Haenssgen a, b, c, d, e, f, *

a. Centre for Tropical Medicine and Global Health, Nuffield Department of Clinical Medicine, University of Oxford, Old Road Campus, Roosevelt Drive, Oxford OX3 7FZ, UK
b. CABDyN Complexity Centre, Saïd Business School, University of Oxford, Park End Street, Oxford OX1 1HP, Oxford, UK
c. Technology and Management Centre for Development, Oxford Department of International Development, University of Oxford, 3 Mansfield Road, Oxford OX1 3TB, UK
d. Green Templeton College, 43 Woodstock Road, Oxford OX2 6HG, UK
e. Economics and Translational Research Group (ETRG), Mahidol Oxford Tropical Medicine Research Unit (MORU), Faculty of Tropical Medicine, Mahidol University,
f. 3/F, 60th Anniversary Chalermprakiat Building, 420/6 Rajvithi Road, Bangkok, Thailand

f. email: marco.haenssgen@ndm.ox.ac.uk, phone: +44 (0) 7771805068

*: Corresponding author
The Struggle for Digital Inclusion: Phones, Healthcare, and Marginalisation in Rural India

Abstract
The gains from digital technology diffusion are deemed essential for international development, but they are also distributed unevenly. Does the uneven distribution mean that not everyone benefits from new technologies to the same extent, or do some people experience an absolute disadvantage during this process? I explore this question through the case study of healthcare access in the context of rapid mobile phone uptake in rural India, contributing thus to an important yet surprisingly under-researched aspect of the social implications of (mobile) technology diffusion.

Inspired by a previous analysis of cross-sectional data from rural India, I hypothesise that health systems increasingly adapt to mobile phone users where phones have diffused widely. This adaptation will leave poor non-adopters worse off than before and increases healthcare inequities. I use a panel of 12,003 rural households with an illness in 2005 and 2012 from the Indian Human Development Survey to test this hypothesis. Based on village-cluster robust fixed-effects linear probability models, I find that (a) mobile phone diffusion is significantly and negatively linked to various forms of rural healthcare access, suggesting that health systems increasingly adapt to phone use and discriminate against non-users; that (b) poor rural households without mobile phones experience more adverse effects compared to more affluent households, which indicates a struggle and competition for healthcare access among marginalised groups; and that (c) no effects emerge for access to public doctors, which implies that some healthcare providers are less responsive to mobile phone use than others.

Overall, my findings indicate that the rural Indian healthcare system gradually adapts to increasing mobile phone use at the expense of non-users. I conclude that rapid mobile phone diffusion creates an opportunity to improve people’s access to healthcare in rural India, but it also creates new forms of marginalisation among poor rural households.

Keywords
Digital inclusion, mobile phones, healthcare, Asia, India, panel data
The Struggle for Digital Inclusion: Phones, Healthcare, and Marginalisation in Rural India

Highlights

- This study relates to the social implications of technology diffusion
- I hypothesise that mobile phone diffusion undermines healthcare access for non-adopters
- I use a panel of 12,003 sick households across rural India in 2005 and 2012
- Poor households have worse access to private care if they fail to adopt during fast diffusion
- Wealthier households and public healthcare access are insulated from this trend
The Struggle for Digital Inclusion: Phones, Healthcare, and Marginalisation in Rural India

Acknowledgements

I thank Proochista Ariana, Felix Reed-Tsochas, Xiaolan Fu, Gari Clifford, Juan F. Castro, Andreas Georgiadis, and participants of the TMCD Research Workshop at the Oxford Department of International Development for helpful discussions and feedback.
The Struggle for Digital Inclusion: Phones, Healthcare, and Marginalisation in Rural India

1 Introduction

It is a common stance that the diffusion of information and communication technology (ICT) is essential for development (Aker & Mbiti, 2010:229; Donner, 2015:14; Heeks, 2008:26), but what if the process of digital inclusion is a struggle that leaves excluded groups worse off than before? I investigate this question through the case study of phone-aided healthcare access in rural India between 2005 and 2012, demonstrating that the increased availability of mobile phones intensifies competition for scarce healthcare services among poor rural households. While poor phone owners enjoy more access to private doctors in contexts of rapid mobile phone diffusion, the slow-growing supply of healthcare and a system that caters increasingly to phone users mean that poor households without mobile phones see their access to healthcare diminish. Left to their own devices, mobile phone adopters thus outcompete non-adopters in the struggle for scarce rural healthcare services.1 All the while, more affluent households with a broader range of options to access healthcare are insulated from these developments.

This research was motivated by the literature on “information and communication technologies and development” (ICTD), which has begun to examine the inequalities of technology adoption (Donner, 2015:137-154; Graham et al., 2014:758-759; Napoli & Obar, 2014; Schroeder, 2015:2828-2830; van Dijk, 2005:22), but which tends to assume that diffusion itself is desirable and that nobody experiences an absolute disadvantage through it. Contrary to this position, an earlier mixed-methods research project on healthcare-related mobile phone use in rural India and rural China suggested that widespread mobile phone use can lead to an adverse over-utilisation of resource-constrained rural healthcare systems, which can leave digitally excluded groups at a growing disadvantage (Haenssgen, 2015a, 2015b, 2015c). Because the cross-sectional study was not designed to capture long-term and systemic effects of mobile phone diffusion, the present paper uses India-wide panel data from the Indian Human Development Survey (IHDS; Desai et al., 2010b; Desai et al., 2016). Adopting a
process perspective of mobile-phone-aided healthcare access, I hypothesise that the increasing spread of mobile phones in rural India worsens healthcare access for digitally excluded households.

This paper contributes to the interdisciplinary study of the social implications of technology diffusion in general, and to the study of digital divides in the field of ICTD in particular. It advances the conceptualisation of digital inclusion through an empirically grounded process framework of technology adoption that appreciates dynamic and systemic effects of mobile phone diffusion on healthcare access in rural, resource-constrained areas. Empirically, it provides the first quantitative evidence that the healthcare access of digitally excluded groups deteriorates with increasing mobile phone diffusion, which challenges the framing of digital inclusion as an unproblematic process. The tools and findings of this paper offer space for further research in other areas of digital development, like employment, government service access, or social interaction.

The remainder of this paper situates the study in the fields of technology adoption and ICTD, followed by a detailed description of the analytical framework (Section 2). Section 3 explains the empirical model to analyse the household panel data from the IHDS, using fixed-effects linear probability models with village-cluster robust standard errors to estimate households’ probability to access healthcare as a function of mobile phone adoption and district-level phone diffusion. The results are described in Section 4, showing that households who failed to acquire a mobile phone between 2005 and 2012 are on average poorer, and that poor households without mobile phones are less likely to gain access to “responsive” private healthcare providers if mobile phones have otherwise diffused widely in their district. Taking into account limitations stemming from the household-level analysis, the imposition of disease categories, and the representativeness of the panel data, Section 5 will argue that the findings correspond to the analytical framework. The results suggest that, on the demand side, diffusion drives competition and creates divides between poor phone users and non-users. On the supply side, healthcare providers who are more responsive to patients’ mobile phone use will increasingly cater to this group at the expense of non-users. That public healthcare access is yet
unaffected by these trends should only offer momentary respite, given that my previous cross-sectional study in 2013-2014 indicated that public providers in rural India have begun to adapt to patients’ mobile phone use, too. Section 6 concludes.

2 Literature and Framework

2.1 Technology Diffusion, ICTD, and Digital Divides in the Context of Mobile Phones

This paper speaks to the literature on digital divides and “information and communication technologies and development” (ICTD) as part of the broader, interdisciplinary study of the social implications of technology diffusion. Two key insights from the broader field—comprising anthropological, sociological, and economic research—are that (a) technology diffusion has both positive and negative consequences for social, economic, and political development; and that (b) these implications are not evenly distributed. The anthropological and sociological literature suggests that distributional variations stem partly from the coevolution between a technology and the society within which it diffuses (Miller, 2010:53). This can entail unforeseen outcomes, as researchers have argued for example that roads create rather than reduce the distance between people (Pedersen & Bunkenborg, 2012:565), clocks have become instruments of control and oppression (Munn, 1992:109; Thompson, 1967:81-86), and new water management technologies alienated previously collaborative communities (Bédoucha, 2002:104).

Given the dialectic relationship between technology and society, it seems indeed improbable that technology diffusion invariably leads to desired development outcomes like improved economic security, education, or political participation (consider e.g. the human development index by the United Nations Development Programme, consisting of income, education, and longevity; UNDP, 2014:160-163). That not all technical change processes are “pro-poor” has been shown for instance by Gudeman (1992:145), who illustrates how continuing innovation and technical change helps Guatemalan households to generate savings and—potentially—profits in the local markets, but their lacking
bargaining power means that more competitive merchants absorb the surplus. And although the
broader economic literature of technology diffusion tends to be more enthusiastic about its potential
benefits (Bandiera & Rasul, 2006:869; Besley & Case, 1993:396; Foster & Rosenzweig, 2010:421),
it, too, is occasionally cognizant of nuances and absences of development outcomes (Stewart,
1978:74).

Within this field, ICTD research focuses on a subset of (typically digital) technologies and their
potential applications to support “development” (variously defined) in low- and middle-income
contexts (Díaz Andrade & Urquhart, 2012:289; Duncombe, 2012:2; Flor, 2015; Heeks, 2014:2; Unwin,
2009:1). As a result, most research in the area of ICTD has focused on ICT readiness and availability,
the factors that drive diffusion and acceptance of technologies, and the positive development potential
of technological change (Andersson & Hatakka, 2013:293; Dodson et al., 2012; Heeks, 2014:12;
Qureshi, 2015:516; Roztocki & Weistroffer, 2014:351). This involves for example the development
and delivery of phone-based interventions in areas like personal finance (Jack & Suri, 2014:220),
aricultural marketing (Rashid & Elder, 2009:5-8), or learning (Aker et al., 2012:118).

The techno-centric focus in ICTD has been criticised for its insufficient emphasis on the social
embeddedness of technology, user behaviour and different forms of use, unintended negative and
positive effects of ICT diffusion, the equity implications of technological change, and the broad
spectrum of consequences surrounding digital inclusion and exclusion (Ayanso et al., 2013:63;
Graham, 2011; Heeks, 2014:12; Sæbø & Furuhol, 2013:128-130; Wyche, 2015:2). The field is only
now experiencing a gradual transition towards broader research of technological and social
development, a growing theoretical base, and more interdisciplinary and mixed-method research that
permits locally grounded conclusions—beginning thus to reflect concerns of the broader study of
technology diffusion (Andersson & Hatakka, 2013; Burrell & Toyama, 2009; Chib, 2015; Donner,
The sub-field of “digital divides” has made a similar transition. The digital divide literature focuses on the uneven adoption of technology, which tends to reproduce or even reinforce inter-personal and inter-societal inequities. Originally framed in terms of ownership of ICT—the “haves” vs. the “have nots” (Barzilai-Nahon, 2006:270; Dewan & Frederick, 2005:299-300; Qureshi, 2014:215; Stump et al., 2008)—the concept would eventually develop into “higher-order” forms of actual engagement with ICTs together with the skills required for their operation (Barzilai-Nahon, 2006:274-275; Helsper, 2012:411-414; May & Diga, 2015:100; Pearce, 2013:78; Robinson et al., 2015; van Dijk, 2006:224). Donner (2015:137-154), Graham et al. (2014:758-759), and Schroeder (2015:2828-2830) go yet further and analyse digital divides between social groups and across countries in terms of technology-aided media content creation and consumption.

While the potentially problematic equity outcomes of technology diffusion are increasingly acknowledged (Mbiti & Weil, 2011:16-17), the process of inclusion is regarded as unproblematic and adoption as generally desirable. For example, Donner, though critical of the distributional implications of global mobile Internet diffusion, argues that, “When we assess the spread of informational production via mobile devices we should not let the (absent) perfect be the enemy of the (nearly ubiquitous) good” (Donner, 2015:153-154). It is thus assumed that diffusion processes benefit various groups differently, but that no party involved in the process will see its living conditions worsen.

I investigate in this paper whether such a positive approach to digital inclusion is defensible. In contrast to previous studies in the field of technology adoption and ICTD, my focus is in particular on population groups who are excluded from the process of mobile phone diffusion. I consider the case of healthcare access in resource-constrained contexts (health being an important domain of development; Sen, 1999), specifically healthcare access in rural India between 2005 and 2012. I derive my hypotheses from an analytical framework that is based on previous qualitative and quantitative research in rural India and rural China (Haenssgen, 2015a, 2015b, 2015c), described in the following section.
2.2 Analytical Framework

2.2.1 Summary

In short, my framework explores the process of digital inclusion and suggests that, as mobile phones diffuse, an already marginalised part of the rural population will be unable to incorporate phones into their health behaviour. Those individuals who are able to do so will for example call a doctor for a home visit or an appointment, have a family member arrange a taxi, or ask friends about sensible treatment options. Within my framework, I expect that such activities entail a shift in patients’ healthcare access towards providers who are more capable of accommodating phone-aided behaviour as part of their service delivery—in rural India, these “responsive” providers more are likely to be private than public doctors as they are not bound to their clinic to carry out a home visit, for example. If an increasing number of patients uses mobile phones in order to access healthcare providers, then this will not only increase demand for healthcare (disregarding here as to whether such demand would constitute an improvement, which it need not necessarily), but the health system will also progressively adapt and cater to this behaviour (e.g. local doctors being only “on call”). Based on this framework, I hypothesise that a health system which adapts to mobile phone use will discriminate increasingly against marginalised and digitally excluded groups.

2.2.2 Incorporating Phones Into Health Behaviour

The process of healthcare-related mobile phone use is depicted as a flow chart in Fig. 1. It shows that, when a patient is ill and requires healthcare access, she will incorporate mobile phones into her healthcare-seeking behaviour if these are generally available, if they are accessible for a health-related purpose, and if they are a suitable solution for the problem at hand. Should these three conditions not hold, the patient will engage in conventional health action without mobile phones. This process is described in detail below.
Even in contexts where mobile phones diffuse rapidly among individuals, households, and communities, people will continue to exhibit diverse arrangements for accessing mobile devices, which means that difficulties in utilising the technology are likely to remain (Burrell, 2010; Chipchase, 2006; Hampshire et al., 2015:97-98; Hampshire et al., 2011:707; Helsper, 2012:411; Karnowski et al., 2011; Katz, 2008:10-11; Reisdorf et al., 2012:15-16; Steenson & Donner, 2009). For example, to “borrow” a mobile phone requires the explicit permission of the owner of the phone and may come
with explicit or implicit costs and obligations for the borrower. In this context, Hahn and Kibora (2008) show that it is customary in Burkina Faso to summon remote family members for funeral arrangements when a villager dies. Phones are borrowed for this purpose from teachers (among others) who live in the village, but the teachers would in return “expect the young men from the village to weed their field” (Hahn & Kibora, 2008:99), which highlights the reciprocal nature and implicit costs of phone borrowing. Similarly, differences in personal characteristics, technical features, technological context, social environment, and local cultures influence how people engage with mobile devices. For example, different mobile phone types and specially designed devices for older users (audio aides, high-contrast displays, simplified navigation) can remedy some of the challenges arising from age-related sensorial impairment (Kurniawan, 2008:893-895; Ziefle & Bay, 2005:381-382).

Whether a phone is indeed accessible for health-related uses also depends on the severity of the patient’s health condition. Difficult access can rule out mobile phone use for what are perceived “trivial” health reasons; common and mild conditions like colds or headaches may neither convince lenders nor justify the social obligations for borrowers to ask for others’ mobile phones. Less pressing health issues, indirect and non-personal access, and less intensive and extensive usage can thus create a disjunction between mobile phone diffusion and phone-aided health action.

Aside from being accessible for a health-related purpose, mobile phones also need to be a suitable solution from the perspective of the patient. My notion of suitability has three interlinked elements. Firstly, the actors and solutions within the health system need to be responsive to phone use, which means that they can be accessed through the phone and provide desirable solutions from the perspective of the patient. If actors in the patient’s surrounding health system are not responsive, accessing them via mobile phones may be futile and the patient has to find other solutions. For example, Pitt and Pusponegoro (2005:145) report the need for emergency ambulance services following a terrorist attack in Jakarta. As an ambulance called for an injured diplomat failed to arrive in good time, “the casualty was taken to hospital in the nearest available form of transport—a rubbish
truck” (Pitt & Pusponegoro, 2005:146). While health system actors as in this case may be unable to respond to mobile phone use, others may actively oppose it. This can have many reasons, including a loss of income sources, concerns about workload, circumvention of institutionalised referral systems, privacy, accountability, and personal safety during home visits (Mechael, 2006:169-170). And although access to such unresponsive providers can also be coordinated without having to interact with them directly (Nakahara et al., 2010:323-325), we may expect that healthcare seeking through the phone is more likely to be practised along the lines of responsive actors in the health system.

Secondly, where the health system can be navigated through viable alternatives to a phone-aided solution, mobile phones are superfluous. Patients are arguably less likely to use a phone if they have preferred health facilities in their immediate vicinity. The World Health Organization (WHO) illustrates such substitutability through emergency care in Ghana: According to a recent report, ambulance services can be accessed “by calling the dedicated emergency line (193) from landlines and mobile phones. However, people can also walk to the ambulance station or make a radio announcement through local FM stations” (WHO, 2010:9). Whether access is unproblematic is then partly a result of availability and location of healthcare providers relative to the patient. Other factors contributing to the substitutability between phone-aided and conventional healthcare access are personal characteristics (e.g. ability to walk or cycle, immediate access to vehicles and caregivers in one’s household) and contextual conditions (e.g. safe roads in good condition, efficient and affordable public transport), which can undermine the instrumental value a mobile phone during an illness. Besides, patients may choose courses of action that are less likely to involve mobile phones, for example self-treatment with medicines at home.

Thirdly, while some individual, contextual, and behavioural factors provide an alternative to health-related phone use, others constitute complementarities that facilitate the realisation of certain types of phone-aided healthcare seeking, for example proper road infrastructure enabling home calls. Some authors for instance suggest that complementary service networks such as taxis need to be
present to enable phone use for emergency transportation (Horst & Miller, 2006:140; Mechael, 2006:121-122; Miller, 2010:128). Likewise, favourable location, public transportation links, and personal vehicle ownership described above as alternatives to home calls can also be facilitators to other activities such as making appointments. While the interplay of alternative solutions and complementarities shapes the visible spectrum of phone-aided healthcare solutions in a given context, it is not clear \textit{a priori} whether the presence or absence of specific assets like vehicles facilitates or discourages phone-aided health action on average.

This process framework suggests that certain parties are possibly excluded from phone-aided health action despite the apparent diffusion of these devices. Digital exclusion of this form is therefore partly a matter of choice (if alternative solutions are dominant), but also of constraint (no phone diffusion, no alignment between phone utilisation and health condition, no responsive provider). Pre-existing patterns of economic, social, and spatial marginalisation can contribute to people falling into the group of “constrained non-users.”

\subsection{Equity Implications of Phone-Aided Health Action}

Fig. 2 considers the implications of the process framework for rural healthcare access. Overall, if patients used to refrain from seeking care or relied on local yet unqualified healthcare professionals \textit{for want of better options}, then mobile phones might enable them to tap into a broader range of solutions, provided that other actors are responsive. The responsiveness of the health system is arguably a function of the diffusion of mobile phones and the associated use of phones among patients for health-related purposes. The light-grey-shaded arrows in Fig. 2 illustrate this: The greater the extent of mobile phone diffusion, the easier it is to use a mobile phone to gain direct access to responsive healthcare providers. Even if a provider does not respond directly to mobile phone use, facilitated logistical arrangements (e.g. taxis) can increase access as well, albeit to a lesser extent.
Fig. 2. Hypothesised Relationship Between Healthcare, Mobile Phone Diffusion, Health Provider Responsiveness, and Digital Inclusion of Patient

Source: Author.

An important implication of this framework is that dynamic health system changes in response to increasing health-related phone use can leave non-users worse off than before, as illustrated by the dark-grey-shaded arrows in Fig. 2. Imagine that a growing number of patients calls responsive doctors to their homes for treatment (e.g. Mechael, 2006:169-170; 2008:98). These healthcare providers would spend an increasing amount of time out of station, making it necessary for other patients to make appointments prior to visiting the clinic. Non-users would consequently experience greater difficulty in navigating the health system, finding “responsive” healthcare providers busy catering to phone users or indeed out of station when they arrive at the clinic. Such developments need not be problematic for individuals who previously had not used mobile phones because of dominant alternatives. As the framework suggests, this group could incorporate phones because their relative value for healthcare seeking rises. However, such developments would be problematic for those people who cannot use mobile phones because of social, economic, or spatial marginalisation, thereby raising the barriers to
accessing healthcare. The ensuing depression of digitally excluded patients’ access to responsive healthcare providers is depicted in the bottom arrow in Fig. 2. To a lesser extent, this “crowding-out” effect would also occur among digitally excluded patients accessing non-responsive providers. This framework suggests that the process of digital inclusion creates an unequal struggle between those patients who are able to use mobile phones to facilitate their healthcare access and those unable to do so.

In summary, my theoretical framework problematizes the process of digital inclusion, suggesting both positive and negative healthcare access patterns associated with mobile phone use and risks of exacerbating the marginalisation of some groups. This is in contrast to the existing digital inclusion narratives, which, even if the outcomes of complete diffusion are understood to be unequally distributed, assume that the process itself is painless and unproblematic. Should it turn out that diffusion instead undermines service access among the rural poor, then the mainstream narratives might require revision.

3 Materials and Methods

This paper uses the case study of mobile phones and healthcare access in rural India (2005-2012) to explore the social implications of diffusion and digital inclusion processes. I base my analysis on recently published panel data from the nationwide Indian Human Development Survey for my analysis (IHDS; Desai et al., 2010b; Desai et al., 2016). The IHDS was carried out in two waves in 2004-2005 and 2011-2012. Wave I included 41,554 households with 215,754 individuals; Wave II surveyed 42,152 households with 204,569 individuals. The panel data structure in the IHDS allows for the matching of households over the two survey periods, yet not of individuals. The analysis therefore involves only those rural households that reported an illness in both survey periods in order to trace healthcare choices over time; that is, 12,003 households per period across 22 Indian states.
I estimate fixed-effects linear probability models with village-cluster robust standard errors, which I explain in the remainder of this section. If healthcare access $Y_{kit}$ is defined as household $i$’s probability of accessing healthcare provider $k$ at time $t$, the empirical specification of the time-demeaned fixed-effects model (with $t_1 = 2005$ and $t_2 = 2012$) is

$$
\bar{Y}_{kit} = \beta_m MOB_{it} + \beta_d DIST_{it} + \beta_x MOB \times DIST_{it} + \beta CONTROLS_{it} + \text{YEAR}_t + \bar{u}_{it}, \quad (1)
$$

Where $\bar{Y}_{kit} = Y_{kit} - \bar{Y}_k$ etc. are time-demeaned variables; $MOB_{it}$ is household-level mobile ownership; $DIST_{it}$ is district-level mobile phone diffusion (as a proxy for health system adaptation to mobile phone use); $MOB \times DIST_{it}$ is an interaction term; $CONTROLS_{it}$ are other household-level, time-variant variables controlling for healthcare access; $\text{YEAR}_t$ is a trend variable; and $\bar{u}_{it}$ is an idiosyncratic error term. Because of time-demeaning (see below), household-specific and time-invariant characteristics drop from the analysis (in the two-period case, the equivalent is achieved by differencing between the survey periods). The dependent and independent variables in this model are summarised in Table 1.

| Table 1. Variables in Regression Models and Expected Relationship to Healthcare Access |
|---------------------------------|----------------------------------------------------------------------------------|
| **Variable** | **Description** |
| $Y_{kit}$ (Dependent Variables) | Any Healthcare: [1] if any ill household member visited any kind of formal or informal healthcare provider; [0] otherwise |
| | Public Care: [1] if any ill household member visited a public doctor; [0] otherwise |
| | Private Care: [1] if any ill household member visited a private doctor; [0] otherwise |
| | Pharmacists: [1] if any ill household member visited a pharmacist; [0] otherwise |
| | Traditional / Other Care: [1] if any ill household member visited a traditional healer or other healthcare provider; [0] otherwise |
| $MOB_{it}$ (HH Mobile Phone) | [1] if household owns at least one mobile phone; [0] otherwise |
| DIST_{it} (District Phone Diffusion) | District-level weighted average share of phone-owning households |
### MOBxDIST\(_{it}\) (Interaction Term)

Interaction term between household-level mobile phone ownership and district-level mobile phone diffusion rate

<table>
<thead>
<tr>
<th>Other Control Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH Landline Phone</td>
<td>[1] if household owns at least one landline phone; [0] otherwise</td>
</tr>
<tr>
<td>HH Average Sex</td>
<td>Percentage of women in household; [1] if 100% women</td>
</tr>
<tr>
<td>HH Size</td>
<td>Number of members in household</td>
</tr>
<tr>
<td>HH Average Age</td>
<td>Unweighted average age of all household members</td>
</tr>
<tr>
<td>HH Below Poverty Line</td>
<td>[1] if per capita household expenditure &lt; poverty line (which varies by state; 2005 poverty line adjusted by village-wise deflator); [0] otherwise</td>
</tr>
<tr>
<td>HH Asset Index(^a)</td>
<td>Unweighted sum of 33 household assets, using the same household asset categories in 2005 and 2012. Stratification of sample by household wealth will categorise households as “poor” if their average assets between 2005 and 2012 were below the unweighted sample median, and as “affluent” otherwise.</td>
</tr>
<tr>
<td>Major Illness</td>
<td>[1] if any household member experienced a “major” disease in last 12 months (e.g. cataracts, tuberculosis, hypertension); [0] otherwise</td>
</tr>
<tr>
<td>Mild Illness</td>
<td>[1] if any household member experienced a “minor” disease in last 12 months (e.g. fever, cough/cold, diarrhoea); [0] otherwise</td>
</tr>
<tr>
<td>No. of Public Health Facilities</td>
<td>Village-level count of public clinics (e.g. sub-centre, primary health centre, community health centre), as recorded in medical facility questionnaire</td>
</tr>
<tr>
<td>No. of Private Health Facilities</td>
<td>Village-level count of private, as recorded in medical facility questionnaire</td>
</tr>
<tr>
<td>No. of Other Health Facilities</td>
<td>Village-level count of other health facilities (e.g. family planning clinic), as recorded in medical facility questionnaire</td>
</tr>
<tr>
<td>Year Dummy</td>
<td>Trend variable, capturing developments e.g. in local infrastructure and overall health service provision</td>
</tr>
</tbody>
</table>

Sources: Author, based on Beals (1976); Colson (1971); Gulliford et al. (2002); Kroeger (1983); Lieber et al. (2006); Meessen et al. (2011); Nyamongo (2002); Shaikh et al. (2008); Shaikh and Hatcher (2005); Storla et al. (2008); van Egeren and Fabrega (1976); Ward et al. (1997).

Notes: HH is household; defined as “people living under one roof and sharing the same kitchen” (Desai et al., 2010a:222).

\(^a\) Wealth index includes mobile phones. Robustness checks excluding phones from index confirmed main results. Robustness checks separating vehicles from wealth index have reproduced the model results without notable differences, while the vehicle coefficient was statistically insignificant for all estimated models. The reported models therefore only include the wealth index.

This analysis involves the estimation of a healthcare access model, which includes mobile phone adoption and diffusion among other determinants of access. Healthcare access takes place in a broader health system, which I define in line with the WHO as a system that incorporates “all organizations, people and actions whose primary intent is to promote, restore or maintain health” (WHO, 2007:2). Access to public and private medical care providers are therefore not the only forms of healthcare utilisation. Informal caregivers and traditional healers should also be considered in healthcare access models, given that they account for up to 90% of all healthcare providers in the health...
systems of some low- and middle-income countries (Sudhinaraset et al., 2013:3). In order to appreciate the multi-actor (or “pluralistic”) nature of the rural Indian health system, the dependent variables I consider access to public doctors and nurses, private clinics, pharmacists, and “traditional and other” healthcare providers, together with overall access to any of these providers. In the empirical models, these are dummy variables that indicate whether any member of the household with a “minor” or “major” illness accessed the respective type of healthcare (conditional on an illness in the household during the twelve months preceding each survey round). Different types of access can take place for the same household at the same time.

As I hypothesise that a health system that adapts to mobile phones will discriminate increasingly against individuals who do not adopt mobile technology, the independent variables of interest relate to household-level mobile phone adoption and health system adaptation to phone diffusion. I use district-level mobile phone diffusion to approximate a state in which a health system may expect people’s mobile phone use to a greater or lesser extent. This variable is calculated as the population-weighted percentage of households who own a mobile phone. In addition, the IDHS data does not include patients’ healthcare-related mobile phone use, but previous research has found that the absence of household mobile phones predicts the absence of phone-aided healthcare-seeking better than the absence personal phone ownership (Haenssgen, 2015b:8). I therefore use household-level mobile phone ownership to approximate the likelihood of household members to engage in health-related phone use. Household phone use and system adaptation may interact insofar as a person using a mobile phone to access a doctor may be more successful in a system that expects such phone use (e.g. by calling taxis, by doctors being ready to accept calls on their mobiles). The interaction term $MOBxDIST_{it}$ captures this relationship.

A positive evaluation of the hypothesis follows if (a) healthcare-related mobile phone use contributes to better access to healthcare, (b) increasing health system adaptation has a negative effect on healthcare access, and (c) the coefficient of the interaction between health-related phone use and
system adaptation is positive, meaning that mobile phone ownership becomes increasingly useful and compensates for the otherwise adverse effects of system adaptation. However, the analytical framework points at space for heterogeneity, as adverse effects may be particularly pronounced for poor households who do not have alternative means of accessing healthcare. In addition, we may expect heterogeneity across different types of healthcare providers, with smaller effects for public providers such as regional hospitals that are bound by institutionalised referral systems and guidelines that prevent phone-based service delivery (Mechael, 2006:169-170).

The empirical model controls for other determinants of access, based on the literature on healthcare seeking and therapeutic itineraries. Important determinants of healthcare access in this literature are the nature, severity, and stage of the specific health condition; the patient’s education, economic situation, age, sex, and decision-making autonomy; personal predispositions and belief systems (e.g. accepting pain as part of lifestyle); societal perceptions of the health condition; availability, accessibility, and awareness about providers (e.g. location); trust in and perceptions of the providers’ quality of care; and the compatibility of provider competences with the patient’s condition (Beals, 1976:184-185; Colson, 1971:234-236; Kroeger, 1983:149; Lieber et al., 2006:469; Nyamongo, 2002:381; Shaikh et al., 2008:749-753; Shaikh & Hatcher, 2005:50-52; van Egeren & Fabrega, 1976:537-538; Ward et al., 1997:21-23).

This long list of determinants suggests that an empirical analysis of healthcare access should be cognisant not only of mobile phone diffusion but also of the patient’s characteristics, her or his social networks and cultural environment, the nature of the illness, and health system attributes. Table 1 displays and describes the control variables that approximate these factors within the IHDS data set. However, it is plausible that unobserved characteristics like health provider preferences are not captured with the IHDS data. In such a case, the error term $\varepsilon_{it}$ in an empirical model could be specified with an idiosyncratic and a household-specific, time-invariant component: $\varepsilon_{it} = a_i + u_{it}$. If the
unobserved household characteristics were correlated with other predictor variables, then this would be a case of an omitted variable problem.

I choose fixed-effects models in order to deal with this problem because, through time-demeaning, the unobservable (assumed static) household characteristics $\tilde{a}_i = a_i - \bar{a}_i$ drop from the model, leaving only the idiosyncratic error term $\tilde{u}_{it} = u_{it} - \bar{u}_i$. Hausman and generalised Hausman tests were statistically significant at the 0.1-percent level for all but two of the estimated models (two affluent sub-sample estimations were statistically significant at the one-percent level), indicating that the fixed-effects specification is preferable to random effects panel models that treat unobserved as uncorrelated with other independent variables.

Because the dependent variable is not normally distributed, logistic regression models are typically preferable to model binary access to healthcare. However, the fixed-effects estimator in a panel logit regression model is likely to be inconsistent where only few time periods are considered—two in the present case (Greene, 2008:801). Considering the problem of inconsistent estimation, I report in this paper only linear probability models with village-cluster robust standard errors (estimations with serial-correlation- and heteroscedasticity-robust standard errors yielded less conservative results and will be omitted here). Robustness checks using fixed-effects logit models yielded results that generally point in the same direction, although significance levels are weakly sensitive to functional form.

Furthermore, it could be argued that the panel containing ill households introduces a sample selection bias. However, the estimation sample containing only sick households in 2005 and 2012 is remarkably similar to the complete panel of rural Indian households, for example in terms of household size (it is on average by 0.3 members smaller in 2005; by 0.2 in 2012) and wealth (on average by 0.10 index units wealthier on a scale from 0 to 33 in 2005; by 0.17 in 2012). In addition, it is plausible to assume that any unobserved household characteristics leading to inclusion into the estimation sample
are controlled for by the fixed-effects estimator. I carried out the analysis using Stata 13 (StataCorp, 2013).

4 Results

4.1 Context and Descriptive Statistics

In order to prepare the multivariate analysis, this section presents descriptive statistics using the IHDS survey sample of households who experienced illnesses in both survey rounds. Summary statistics of this sample are presented in Table 2.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>Mean</td>
<td>Std. Dev</td>
</tr>
<tr>
<td>HH Mobile Phone</td>
<td>12,003</td>
<td>0.03</td>
<td>0.17</td>
</tr>
<tr>
<td>District Phone Diffusion</td>
<td>264</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>HH Landline Phone</td>
<td>12,003</td>
<td>0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>HH Size</td>
<td>12,003</td>
<td>6.38</td>
<td>3.25</td>
</tr>
<tr>
<td>HH Highest Educationb</td>
<td>12,003</td>
<td>1.97</td>
<td>1.53</td>
</tr>
<tr>
<td>HH Average Sex (1=Female)</td>
<td>12,003</td>
<td>0.49</td>
<td>0.16</td>
</tr>
<tr>
<td>HH Average Age</td>
<td>12,003</td>
<td>28.23</td>
<td>10.89</td>
</tr>
<tr>
<td>HH Below Poverty Linec</td>
<td>12,003</td>
<td>0.22</td>
<td>0.41</td>
</tr>
<tr>
<td>HH Asset Indexd</td>
<td>12,003</td>
<td>9.68</td>
<td>5.14</td>
</tr>
<tr>
<td>Any HH Member, for Any Illness</td>
<td>12,003</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Accessed Any Healthcare</td>
<td>12,003</td>
<td>0.96</td>
<td>0.19</td>
</tr>
<tr>
<td>Accessed Public Care</td>
<td>12,003</td>
<td>0.31</td>
<td>0.46</td>
</tr>
<tr>
<td>Accessed Private Care</td>
<td>12,003</td>
<td>0.69</td>
<td>0.46</td>
</tr>
<tr>
<td>Accessed Pharmacist</td>
<td>12,003</td>
<td>0.06</td>
<td>0.23</td>
</tr>
<tr>
<td>Accessed Traditional/Other Care</td>
<td>12,003</td>
<td>0.03</td>
<td>0.16</td>
</tr>
<tr>
<td>Minor Illness in Past 12 Months</td>
<td>12,003</td>
<td>0.83</td>
<td>0.38</td>
</tr>
<tr>
<td>Major Illness in Past 12 Months</td>
<td>12,003</td>
<td>0.43</td>
<td>0.50</td>
</tr>
<tr>
<td>No. of Public Clinicsa</td>
<td>1266</td>
<td>0.89</td>
<td>0.35</td>
</tr>
<tr>
<td>No. of Private Clinicsa</td>
<td>1266</td>
<td>0.93</td>
<td>0.33</td>
</tr>
<tr>
<td>No. of Other Clinicsa</td>
<td>1266</td>
<td>0.09</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Notes: Unweighted statistics. First difference morbidity statistics for households who experienced a minor/major illness in both survey rounds. HH is household.

- District-level data (rural areas only), calculated as weighted average share of phone-owning households in districts, using complete survey sample and village sampling weights.
- 0=“illiterate,” 1=“uncompleted primary education,” 2=“completed primary education (5< class),” 3=“completed middle school (8< class),” 4=“completed secondary education (10< class),” 5=“completed higher secondary education (12< class).”
- 1= per capita household expenditure < poverty line (which varies by state; 2005 poverty line adjusted by village-wise deflator).
- 1 Unweighted sum of 33 household assets, using the same household asset categories in 2005 and 2012.
- Village-level data, as recorded in medical facility questionnaire.
As is evident from the table, mobile phones have spread rapidly across rural India between 2005 and 2012. The average share of households owning a phone in the sample has increased from 3% to 75% over the study period from 2005 to 2012. An average district in the study sample experienced an increase of 70 percentage points in the absolute proportion of rural households owning a mobile phone, with an inter-quartile range of 62-81% (a histogram depicting the increase is shown in Fig. 3). At the same time, the share of households owning a landline phone dropped from 11% to 5%.

![Absolute change in district phone diffusion, 2005-2012](image)

**Fig. 3. Change in District-Level Mobile Phone Diffusion in Survey Sample, 2005-2012**

Source: Author, derived from Desai et al. (2010b, 2016).

Notes: Based on 264 districts represented in estimation sample.

Other socioeconomic indicators also indicate notable change over time. For example, the average survey household became smaller and was 3.7 years older in the second survey round. Wealth increased by 29% from 9.7 to 12.5 common household items, and the share of households below the poverty line fell 3 percentage points (based on inflation-adjusted state-level poverty lines and per-capita household expenditure).
In terms of healthcare, overall utilisation rates of informal and formal healthcare providers were very high with 97% in 2012, up 1% from 2005. Private healthcare was with 71% in 2012 the most commonly accessed type among the rural households in the survey, while traditional and other forms of healthcare provision only accounted for 4% of the sample in 2012. Access to all categories of healthcare providers increased between 1 (traditional healers) and 4 (public doctors) percentage points over the two study periods. As far as the supply of health facilities is concerned (considering that IHDS does not contain an exhaustive census of health facilities), village-level facility survey data from the IHDS indicates that the provision of public clinics increased slightly from an average of 0.89 to 0.90 facilities per village (corresponding to a decrease from 12.0% to 10.6% of villages without any public clinic). Private facilities were commonly found in the survey villages as well but their average number (together with “other” clinics e.g. for family planning) fell marginally over the same period. Overall, the survey context is one in which households experienced a notable increase in socio-economic indicators, situated in an environment of high healthcare demand and constant supply.

The analysis in the remainder of this paper will make the claim that mobile phone diffusion has undermined healthcare access for marginalised groups at the expense of more affluent households. In order to establish that mobile phone owning households are better off than their “disconnected” peers, Table 3 presents the levels and changes of household assets and poverty status, depending on whether a household owned a mobile phone in 2005 and 2012. The table shows that households who did not own a phone in either period had the highest poverty incidence and the lowest wealth, the latter of which expanded below the sample average. In contrast, households who acquired a phone between 2005 and 2012 developed their asset wealth by 3.7 units (2.7 if adjusted for mobile phones as index component), notably above the sample average of 2.8 (2.1). In light of these patterns, we can establish that households who had not acquired a mobile phone by 2012 were economically more marginalised than those who did.
### Table 3. Wealth and Poverty Trends by Household Mobile Phone Ownership

<table>
<thead>
<tr>
<th>Phone in 2005</th>
<th>Phone in 2012</th>
<th>Number of Households in Panel</th>
<th>Average Household Asset Index</th>
<th>% of Households &lt; Poverty Line</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2005 (adjusted)*</td>
<td>2012 (adjusted)*</td>
<td>Difference (adjusted)*</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>22 (0.2%)</td>
<td>16.5 (15.5)</td>
<td>11.9</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>2,987 (24.9%)</td>
<td>6.6</td>
<td>7.2</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>340 (2.8%)</td>
<td>19.7 (18.7)</td>
<td>20.6 (19.6)</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>8,654 (72.1%)</td>
<td>10.3</td>
<td>14.0 (13.0)</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>12,003</td>
<td>9.7 (9.7)</td>
<td>12.5 (11.7)</td>
</tr>
</tbody>
</table>

* Households mobile phone ownership is a component of the household asset index. Acquiring the first household phone corresponds to a one-unit increase in the index.

#### 4.2 Regression Results

This section presents the results of the fixed-effects linear probability models. As indicated in Section 3, I estimate 15 models, five each for the general rural population of India, for rural households below median income (“poor”), and for rural households above the median income (“affluent”). For each group, I estimate a model of overall access to any healthcare provider, and provider-specific models for access to public doctors, private doctors, pharmacists, and to traditional and other healthcare providers. The main independent variables in these models are household-level mobile phone ownership, district-level mobile phone diffusion, and an interaction term between these two variables. The linear probability model results are shown in Table 4, all of which are significant at the 0.1-percent level. I focus the examination of the results on overall access to healthcare and access to public and private providers among poor households, which represent the most common forms of healthcare utilisation.
### Table 4. Fixed-Effects Linear Probability Regression Results: Factors Influencing Change in Rural Healthcare Access

<table>
<thead>
<tr>
<th></th>
<th>All Rural Households</th>
<th>Poor Households (&lt;Median Wealth)**</th>
<th>Affluent Households (&gt;Median Wealth)*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>HH Mobile Phone</td>
<td>-0.02</td>
<td>0.05</td>
<td>-0.05</td>
</tr>
<tr>
<td>District Phone Diffusion</td>
<td>-0.10***</td>
<td>0.06</td>
<td>-0.12</td>
</tr>
<tr>
<td>MOBxDIST Interaction</td>
<td>0.03</td>
<td>-0.09</td>
<td>0.11*</td>
</tr>
<tr>
<td>HH Landline Phone</td>
<td>0.00</td>
<td>0.05**</td>
<td>-0.04</td>
</tr>
<tr>
<td>HH Highest Education</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>HH Size</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>HH Average Sex (%) Female</td>
<td>-0.04**</td>
<td>-0.02</td>
<td>-0.08*</td>
</tr>
<tr>
<td>HH Average Age</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00*</td>
</tr>
<tr>
<td>HH Below Poverty Line</td>
<td>-0.01</td>
<td>0.01</td>
<td>-0.05***</td>
</tr>
<tr>
<td>HH Asset Index</td>
<td>-0.01***</td>
<td>-0.00***</td>
<td>-0.01***</td>
</tr>
<tr>
<td>Minor Illness in Last 12m</td>
<td>0.07***</td>
<td>0.08***</td>
<td>0.16***</td>
</tr>
<tr>
<td>Major Illness in Last 12m</td>
<td>0.02***</td>
<td>0.12***</td>
<td>0.13***</td>
</tr>
<tr>
<td>No. of Public Clinics</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.02</td>
</tr>
<tr>
<td>No. of Private Clinics</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.04*</td>
</tr>
<tr>
<td>No. of Other Clinics</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.04*</td>
</tr>
<tr>
<td>Year 2012 Dummy</td>
<td>0.08</td>
<td>0.02</td>
<td>0.11***</td>
</tr>
<tr>
<td>Constant</td>
<td>0.81</td>
<td>0.23***</td>
<td>0.45***</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>24,006</td>
<td>24,006</td>
<td>24,006</td>
</tr>
<tr>
<td>R² (Within)</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Model Test (p &gt; F)</td>
<td>&lt;0.000</td>
<td>&lt;0.000</td>
<td>&lt;0.000</td>
</tr>
</tbody>
</table>

Notes: HH is household.

* “Poor” and “affluent” categorised as below/above median wealth index, using average unweighted household wealth between both survey periods.

*p<0.05, **p<0.01, ***p<0.001.
The results allow three main observations. First, the table shows that mobile phone diffusion is associated with changes in overall healthcare access (general population and poor sub-sample), private healthcare access (general population and poor sub-sample), access to pharmacists (general population and both sub-samples), and access to traditional and other healthcare providers (affluent sub-sample). Public healthcare access appears to be independent of mobile phone diffusion on the household and district levels, and the relationship between mobile phones and healthcare access appears to be weaker for affluent households. These differences across healthcare providers, and especially the response of private clinics, corresponds to my argument that some actors in the health system are more responsive to mobile phone use.

Secondly, poorer households show a negative link between district-level mobile phone diffusion and overall healthcare utilisation (Model 6, significant at the five-percent level) and access to pharmacists (Model 9, significant at the one-percent level). The regression coefficients suggest that a 10 percentage point increase in district-level mobile phone diffusion is linked to a 1.5 and 1.3 percentage point decrease in overall healthcare and pharmacist access for the poor household sub-sample (1.0 and 1.3 percentage point decrease for the overall sample). The relatively weaker effect for the affluent subsample corresponds to my notion that richer households have more means to access healthcare, which reduces their need for mobile phones and insulates them from potentially adverse consequences.

Thirdly, the effect of district-level mobile phone diffusion on poor household’s access to private clinics varies depending on whether a household owns a mobile. The interaction term in Model 8 is statistically significant at the one-percent level. As the interaction term is positive while the coefficients of the interacting variables are both negative, the results indicate that the negative relationship between private healthcare access and household-level mobile phone diffusion becomes “more positive” as mobile phones diffuse more widely in the district. In addition, the effect of a household mobile phone is initially negative, but higher degrees of district-level diffusion have a
positive effect for households owning mobile phones, leading to a combined effect that gradually increases and exceeds households without mobile phones at approximately 57% district-level diffusion. However, any linear combination of the coefficients remains negative (numerically, it would only turn positive if around 180% of a district’s households had acquired a phone). These patterns correspond to the hypothesised idea that the value of using a mobile phone changes in a system that adapts to such use (see the discussion in Section 5 why the average effect could be negative).

As far as other control variables are concerned, the coefficient for landline phones suggests that households seek more access to public doctors if their household acquires a landline phone connection. But we also need to appreciate that the portion of households owning a landline phone decreased from 11% to 5% across the study periods, and that landlines are less likely to be installed in remote locations, so the coefficients indicate that a household is less likely to access public healthcare if it loses its landline connection. For poorer households, with the exception of disease severity and the constant term, none of the control variables for public healthcare access are significant at the five-percent level. Aside from mobile phones, growing households and those surpassing the poverty line become more likely to access private healthcare.

In order to explore the relevance of these results, it is instructive to compare the predicted effects of mobile phone diffusion across all rural households and the poor sub-sample. For example, linear predictions based on Models 1 and 6 suggest that an increase of district-level mobile phone diffusion from 25% to 75% corresponds to a decrease in any kind of healthcare access from 98% to 93% for all rural households that experienced an illness, and from 96% to 90% for poor households. Access to pharmacists would decrease from 9% to 3% for both groups in these scenarios.

The relationship between private healthcare access and mobile phone diffusion is less straightforward, due to the interaction term. For the sample of all rural households, the linear predictions suggest that a household without a mobile phone would see its probability to access a private doctor decrease from 70.5% in a district with 25% diffusion to 64.8% in a district where 75%
of households own a phone. In contrast, a household with a mobile phone would see its probability
virtually unchanged at 68.6%. The differences are yet more pronounced for poor households, where a
similar expansion of district-level mobile phone diffusion would be associated with a decrease from
70.0% to 60.3% for households without mobile phones, and an increase from 60.9% to 65.1% for
households who own a mobile.

Fig. 4 visualises the predicted probability of a household to access private doctors (y-axis),
depending on household wealth (Panel a for all rural households, Panel b for poor households), on
household-level mobile phone ownership (dark-grey markers for households without, light-grey
markers for households with mobile phones), and on the extent to which mobile phones have diffused
on the district level (x-axis). The predictions indicate that households without mobile phones have
decreasing access to private doctors in districts where mobile phones have diffused more widely, and
this decrease is particularly pronounced for the poor rural households in Panel b. In contrast, the
probability of access is independent of diffusion rates if the household has a mobile phone—which
could mean that owning a mobile phone helps to prevent a deterioration in access—and a poor
household with a mobile phone is increasingly likely to access healthcare if phones have diffused more
widely.
Overall, these results support the hypothesis that non-users of mobile phones have less access to healthcare in contexts where mobile phones have diffused rapidly. Poor households’ access to overall healthcare, to private doctors, and to pharmacists is negatively linked to mobile phones diffusion either on the district level or personal level. In contrast, affluent rural households’ healthcare access is largely independent of these developments.

5 Discussion

While I have already hinted at a possible interpretation of the results in the previous section, it is important to consider at least three important limitations of the analysis before discussing its significance. These limitations pertain to the imposition of disease severity classifications, the representativeness of the panel data, and the level of analysis and its associated measurement challenges.

Firstly, it could be considered problematic that the severity of illness, which controls for households’ healthcare access, is defined by the survey agency rather than by the respondents themselves. Individuals’ initial decisions to seek care are more likely to be driven by their own observations and socially agreed notions of appropriate health action than by later diagnoses by doctors and researchers (Beals, 1976:184-185; Gulliford et al., 2002:187). While this may skew the predictive power of control variables for “minor” and “major” illnesses, they remain statistically significant and improve model fitness. Robustness checks that replaced binary disease severity indicators with the number of household members with “minor” and “major” illnesses did not affect the results.
Secondly, the panel is not a representative sample of all rural Indian households over time, but rather of those whose members experienced illnesses repeatedly across the survey periods. The panel structure used in this study enables an analysis of how households with sick members change their behaviour in a dynamic mobile diffusion context, but it leaves open the question as to how an “average” household would behave, given that only 60.2% of the household sample reported an illness in 2005, and 71.7% in 2012. For example, mobile phone may enable some people to recognise a discomfort as an illness (or vice versa). Nevertheless, average household characteristics of the full rural sample are similar to the panel of ill households (see Section 3), and the household-fixed-effects analysis controls for unobserved, time-invariant household characteristics. This makes it plausible that deviations from average rural household behaviour in India are minor.

Lastly, and perhaps most importantly, the panel data of the IHDS only permits a household-level analysis of healthcare access and mobile phone use, which limits the depth of the analysis. In the present case, household-level healthcare access as a binary variable obscures the potentially sequential logic of healthcare-seeking behaviour (Balabanova & McKee, 2002; Kibadi et al., 2009; Moshabela et al., 2011; Shaikh et al., 2008), the nature of potentially collective healthcare decision-making (Peglidou, 2010:49), and, as a variable of “revealed behaviour,” only captures successful access and ignores whether an individual “sought” but failed to obtain healthcare. Likewise, household-level mobile phone ownership maps only imperfectly onto individuals’ actual health-related use of a mobile, be it directly by the patient or mediated through a third person. In this respect, approximating health-related mobile phone use through household phone ownership (or, more precisely, approximating the absence of such use through the absence of a household mobile; Haenssgen, 2015b:8) also creates the impression that very few non-users remain at near-100% district-level diffusion, which need not necessarily be the case. Although these complications mean that the estimated models are only an imperfect representation of the actual relationship between healthcare access and phone usage, I am nonetheless able to discern effects that are consistent with the empirically grounded hypothesis that
non-users of mobile phones are worse off in contexts of fast diffusion. However, a more fine-grained
analysis would require higher-frequency panel survey data geared specifically towards individuals’
health-related mobile phone use and health system actors’ capacity to absorb the demand from phone-
using patients.

In light of this discussion, considering that the linear probability models control for unobserved
heterogeneity while focusing on the change within households, and given that the panel regression
results correspond to hypotheses and findings derived from primary rural Indian survey data
(Haenssgen & Ariana, 2015), I have reason to trust the robustness of the results and the causality
running from changes in household- and district-level mobile phone adoption to households’
healthcare access. The identified relationship between district-level mobile phone diffusion and
household-level healthcare access suggests that health systems adapt to increasing mobile phone use,
which gradually improves the effect of a household mobile phone for rural households’ access to
private healthcare. In the absence of a household mobile phone, poor households in districts with fast
mobile phone diffusion are less likely to access such healthcare. I see this as evidence that rapid mobile
phone diffusion can reinforce rather than ameliorate existing patterns of marginalisation, given that
digitally excluded households tend to be poorer on average.

Drawing on the initial explanatory framework, the findings can be explained through factors
on the demand as well as the supply side. On the demand side, mobile phone use appears to contribute
to healthcare access, enabling for example the ability to arrange home visits of doctors, to make
appointments, call a taxi, or simply to talk with relatives about treatment options (note that increased
access need not entail improved health outcomes). Not all but some households will make use of this
option, especially if it is the dominant strategy compared to alternative solutions, such as walking for
half an hour to a health post. Where such dominant phone-aided strategies among otherwise access-
constrained poor households exist, they increase their competitiveness relative to poor households
without mobile phones. This would bear resemblance to patterns observed in other contexts, for
instance the UK middle class reportedly exercising their “sharp elbows” towards other health system
users and thereby contributing to the reinforcement of healthcare inequities vis-à-vis poorer and more
vulnerable population groups (Seddon, 2007:88). Mobile phone users would therefore increasingly
join the “healthcare middle class,” which is populated customarily by more affluent rural households
who face fewer healthcare access constraints and a wider range of choices, both of which insulate them
from the effects of mobile phone adoption and diffusion. As the data suggest, poor mobile phone users
gravitate towards the rural average level of private healthcare access in situations where phones have
diffused widely. The group losing the competitive struggle comprises households who are prevented
from adopting mobile technology. On the demand side, mobile phones therefore appear to create new
divisions and emerge as a somewhat regressive tool that benefits the “better-off” poor rural population.

The demand-side reactions interact with developments on the healthcare supply side. In
particular, the improved effects of phone ownership in contexts of fast mobile phone diffusion suggests
that health systems adapt to increasing mobile phone use and thus privilege phone-aided healthcare-
seeking strategies. But not all elements of the health system react equally to these developments. Public
health service access has not been affected, thanks probably to variations in responsiveness across
different health system actors. However, this may soon change, as my qualitative and quantitative
research in rural Rajasthan in 2013 and 2014 has indicated that local public doctors and nurses (based
in sub-centres and primary health centres) increasingly use mobile phones in their everyday work
(Haenssgen, 2015c). Flexible working conditions for local government providers (e.g. nurses and
village doctors) and gradually evolving guidelines that encourage health centre staff to deal with
patients’ mobile-phone-aided healthcare behaviour suggest that public healthcare might not be
protected from patients’ competitive pressure for much longer.

Although these findings correspond to my analytical framework, a remaining puzzle is the
average negative effect of mobile phone diffusion on healthcare access. A possible interpretation of
this pattern may be related to social capital. Qualitative and quantitative sociological research around
the world, which has made the claim that mobile phones enable people to uphold relationships with close contacts with “strong” ties, but that they do not necessarily lead to more communication among networks with “weak” ties and that they may even enable people to avoid their immediate social environment (Horst, 2006:147-148; Ling, 2008:106; Miritello et al., 2013:93-94; Saramäki et al., 2014:946). Accordingly, mobile phones might enable rural Indian villagers to maintain relationships with family members and close social contacts across villages, but these improvements come at the expense of eroding local social capital. If this argument holds, then phone diffusion might reduce people’s ability to find help locally. However, because this explanation was not part of my framework and cannot be tested with the present data set, it remains speculative and subject to further research.

Taken together, this is a considerable challenge for common narratives of digital inclusion. As one group increasingly “benefits” from mobile phone use and an adapting environment, another loses because healthcare supply does not pick up accordingly. This group—already poor—becomes increasingly marginalised in contexts of otherwise rapid mobile phone diffusion. Indeed, during the process of diffusion, one may have to become digitally included in order to maintain the same relative position in healthcare access. At the same time, where mobile phones have not diffused rapidly, acquiring one need not necessarily mean better access to services if the service providers are not responsive to phone use.

6 Conclusion

Challenging the framing of “digital inclusion” as an unproblematic process, this paper explored the relationship between mobile phone diffusion and rural Indian households’ access to healthcare. Based on previous research in rural India, I hypothesised that households without mobile phones are increasingly disadvantaged in their healthcare access if mobile phones diffuse rapidly in their environment. This assumed that health systems comprise actors with different degrees of “responsiveness” to mobile phone use, and that increasing phone diffusion leads these responsive
providers to expect health-related phone use among the population. Fixed-effects linear probability
models with village-cluster robust standard errors using nationwide panel data from 2005 and 2012
lend support to this hypothesis: District-level mobile phone diffusion is negatively linked to rural
households’ healthcare access, especially for poor households who tend to face more constraints, and
for private healthcare providers who tend to be more responsive to health-related mobile phone use.

Contrary to its common depiction, the process of digital inclusion delivers tools that intensify the
competition for scarce healthcare resource among deprived populations. These conditions indicate that
new phone-based technologies may help a broad part of the population to gain access to services, but
they are unlikely to include the most marginalised groups. Yet, acquiring a phone before everyone else
need not be advantageous either if the system cannot respond to its usage.

While the conclusion might look like we need more mobile phones for poor people in order to
keep them “competitive” and maintain or enhance their access to healthcare, there are two important
points that challenge this argument. First, the households who had not managed to acquire a mobile
phone are increasingly pressured to do so in order to maintain the same level of healthcare access at a
higher level of competition (note the resemblance to Lewis Carroll’s Red Queen’s race; Carroll,
1872:42), which is akin to a “tyranny” of technology adoption. This would not be the first argument
of its kind, as authors like Rich Ling argue that mobile technology has indeed now become so pervasive
in some domains of Western urban life that it is simply expected of everyone to use it so as to not
inconvenience others (Ling, 2012:178-179). In such situations, technology adoption stops being a free
choice. Second, more access to healthcare is not the same as access to better healthcare. The gradual
democratisation of health system utilisation can instead entail unnecessary treatment for minor
ailments, bypassing of referral systems put in place to ensure efficient health system operation, and
possible shifts away from less to more responsive healthcare providers with implications for the quality
of care received (Haenssgen, 2015a). I suggest that, in the struggle created during the process of digital
inclusion, persistently excluded parties require protection through conventional means such as efficient
public transport links, dependable and convenient clinic hours in local health centres, and guidelines
preventing healthcare providers to privilege patients accessing them through mobiles. Where mobile
phone use reduces the costs of public health service delivery, these savings can be put usefully towards
sustaining the healthcare access of more vulnerable parts of the population.

This study invites a number of questions for future research. Considering the nature of the
household panel, one of the more immediate questions is whether individual-level healthcare-seeking
panel data can shed further light on the implications and nuances of mobile phone diffusion in India.
Broader questions from a comparative perspective would investigate whether the experience of rural
India is generalizable, and, if not, what individual, social, infrastructural, technological, and health
system factors contribute to the mitigation and amplification of such effects. But struggles in the
process of digital inclusion might not be unique to healthcare, which raises the possibility that other
domains of digital development are affected as well. This might in particular be the case where mobile
phone use skews demand for scarce resources, for example employment, governmental services, or
time with social contacts. In addition to these mostly empirical considerations, further work to theorise
the social implications involved in the process of technology adoption is necessary to move away from
an idealised notions of inclusion. As Tim Unwin’s book *ICT4D* opens with the lines “This book is
about how information and communication technologies (ICTs) can be used to help poor and
marginalised people and communities make a difference to their lives” (Unwin, 2009:1), perhaps we
should also start reflecting on how we can prevent ICTs from making poor and marginalised people’s
lives worse.
References


StataCorp. (2013). Stata Statistical Software: Release 13. College Station, TX: StataCorp LP.


doi:


Endnotes

1 The term “adopter” here implies that a mobile phone is being used for a health-related purpose. Theoretically, owning or using a phone in general might not necessarily entail health-related uses.

2 See for example Schroeder (2010:80-81) on complementarities between of mobile phones and other ICTs in the context of social interaction, and Fu and Polzin (2010:326-327) on a discussion of “complementary assets” in a developing-country enterprise setting.

3 Households that split over the study period are included as duplicates in the 2005 survey in order to not bias the sample towards growing and stable units. The assumption of this procedure is that descendants from one household share the same beliefs as the original unit.

4 While tempting, robustness checks using the share of sick household members who accessed a particular kind of healthcare provider conflate intensity of care-seeking with overall exclusion and are therefore less suitable for this estimation.

5 Unweighted statistics; based on cleaned panel data set of 26,517 households each in 2005 and 2012, compared to 12,003 households in the estimation sample.

6 Note that the coefficients in the models are identified by the change within households’ conditions, with invariant variables on the household level dropping from the estimation.